Addis Ababa Science and Technology University

College of Electrical and Mechanical Engineering

FUZZY MODEL PREDICTIVE CONTROL FOR BIOMASS BOILER

By

Getinet Asimare

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Advisor:

Prof. Venkata L.N.M

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Certificate

This is to certify that the thesis prepared by **Mr. Getinet Asimare Nibiret** entitled "**Fuzzy Model Predictive Control for Biomass Boiler**" and submitted in fulfillment of the requirements for the Degree of Master of Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Declaration

I hereby declare that this thesis entitled "**Fuzzy Model Predictive Control for Biomass Boiler**" was composed by myself, with the guidance of my advisor, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted, in whole or in part, for any other degree or professional qualification.

Name: Getinet Asimare Nibiret

Signature: ………………….

Date: 30 /01/2019

This thesis has been submitted for my approval as a university advisor.

Name: Prof. Venkata L.N.K

Signature: . Kvlnarayana …

Date: 30 /01/2019

Abstract

Biomass has a great significance in the field of renewable energy sources. Biomass boiler unit that produce steam is one of the critical component of power plant. It is a highly coupled multivariable process which is nonlinear in nature. The conventional controllers which are used in the industry are not efficient control techniques for coupled systems. In this thesis work model predictive controller is proposed to overcome the coupling of variables in biomass boiler plant. Fuzzy modeling is a technique that used to model the biomass boiler which is capable of approximating the nonlinear function to linear. The proposed technique is implemented using MATLAB/Simulink and FMID tool box for system identification. The measured input output data is gathered from Wenji-Shoa sugar factory for fuzzy model identification. The proposed model predictive controller has achieved shorter settling time of 10 second and acceptable overshoot which is 0.5% and 0.39% for pressure and temperature respectively.

Key words: Fuzzy identification, Fuzzy Modeling, Model Predictive Control.

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Contents

List of Tables

List of Figures

List of Acronyms

MIMO…………………………Multi input Multi output

MISO…………………………. Multi input Single output

PID …………………………… Proportional + Derivative + Integral

MPC ……………………………Model Predictive Controller

NMPC ………………………… Nonlinear Model Predictive controller

RGA ……………………………Relative Gain Array

UN ……………………………..United Nation

FIS ……………………………..Fuzzy Inference System

PI ……………………………….Proportional + Integral

DCS …………………………….Distributed Control System

PLC …………………………….Programmable Logic Controller

LTI ……………………………..Linear Time Invariant

FMPC ………………………….Fuzzy Model Predictive Control

ID ………………………………Induced Draft

FD ………………………………Forced Draft

NARX …………………………. Nonlinear Autoregressive with Exogenous Input

GK ……………………………..Gustafson Kessel

FCM ……………………………Fuzzy Clustering Method

IMC …………………………....Internal mode Control

GPC …………………………….Generalized Predictive Control

CARIMA ………………………..Integrated Controller Auto Regressive Moving Average

Chapter one

1. Introduction

Boiler unit that produce steam is one of the critical components of the power plant. Because the measured variables of boiler which are the steam flow rate, temperature and pressure affect the performance of the power plant. It has different heat sources such as biomass, coal, fossil fuel and electric power.

Biomass has great significance in the field of renewable energy. Most countries in the world showed their willingness to reduce emission of CO_2 and other greenhouse gases at the latest UN climate change conference in Cancun 2010. This indicates that renewable energies such as biomass will gain more and more importance in power production [1]. Ethiopia is one of the countries that use biomass as source of energy. It covers 3% of the total biomass energy usage and has 7th rank among them [2]. The biomass resource originated from forests and agriculture is the oldest but usable form of renewable energy. Biomass is defined as non-fossil, organic material with biological origin having intrinsic chemical energy content. Biomass for fuel is considered to be carbon free. Plants remove and store carbon dioxide from the atmosphere while they grow [3]. When we burn them for different application like power and heat generation the stored carbon dioxide is released to the environment and will cause unbalanced carbon content in the environment. However, it can be solved by growing a new plant which can recaptured again the released gas. There for biomass is the best renewable source of energy.

Model predictive control (MPC) is one of the most researched synthesis approaches which is based on a model of a process, computes the best control strategy according to a set of predefined goals over a future time horizon. While traditionally, control systems determine the course of actions based on the evolution of the error of previous iterations. MPC is driven by evaluating the expected future error due to a chosen control trajectory in a receding horizon fashion [4]. The success of MPC is in part due to the following factors:

- Applicability to a broad class of systems which are difficult to control (i.e. process with significant time-delays or non-minimum phase behavior)
- Ability to handle constraints imposed in the control as well in the system states
- Algebraic approach to obtain a closed-loop controller
- Easily extended to MIMO processes
- Good reference tracking performance

Fuzzy inference system (FIS) are universal approximators capable of approximating any continuous function with a certain level of accuracy [5]. The FIS are based on the so-called IF-THEN rules and are classified in to two main categories: Mamdani models and Takagi-Sugeno models. Takagi-Sugeno model will be implemented in this work.

1.1. Statement of Problem

Ethiopia uses 3% of the total amount of biomass in the world for energy purpose. It has 7th rank among the countries which uses biomass as energy sources. Its known that sugar factories are one site of power production from biomass fuel. Biomass boiler is steam generator which uses biomass as a source of heat. However, the controlling mechanism of biomass boiler in sugar factories is not efficient, because they use manual controlling and automatic control like programmable logic controller integrated with PI controller.

As known biomass boiler is highly nonlinear and multivariable process due to the coupling of variables such as temperature, pressure, fuel flow, air flow, steam drum level and other variables. Since it is transient process it should be controlled efficiently with predictions of future values in order to get good reference tracking response.

The reviewed literatures showed that many modeling and control algorithms are applied to improve biomass boiler efficiency. As example the dynamic model which is nonlinear is linearized at some specified working region by finding operating point. However, this may lead to cause high modeling error as well as the dynamics of the boiler may not be fully known since it is complex. Some of control algorithms uses linear system identification for biomass boiler, which leads to ill conditioned controlling (low accuracy) since the system is highly coupled and nonlinear. On the other hand, the modeling and control algorithms which are conducted previously manly covers only one or two variables by ignoring interaction of variables in the system.

To solve the problem of control mechanism PI, adaptive PI and PLC are applied widely. However, since PLC is logic based control it is based on the current measurement of the system which cannot predict the future condition of the system and it cannot handle the constraints. PI controller needs decoupling of the system into single input single output, while this leads to loss of variables and interactions. Generally, these controllers cannot handle constraints in order to save energy and have no optimization problem.

1.2. Objectives

1.2.1. Main objective

The main objective of this thesis work is to develop a fuzzy model based predictive control for biomass boiler system.

1.2.2. Specific objectives

- To obtain the mathematical model of Biomass Boiler system from the gathered data by using system identification tool.
- To design a MPC (model predictive controller) for the Biomass Boiler systems
- To tune the MPC (model predictive control) in each set point to obtain good performance

1.3. Methodology

This work begins with reviewing related works with Biomass Boiler and model predictive controller. In this season different international journals and different other related papers are studied which are presented in chapter two. After reviewing literatures, the measured data is gathered from Wenji-Shoa sugar factory. Then the model of the Biomass Boiler is identified by using fuzzy modeling and identification toolbox. And this identified model is linearized globally by using weight factors. After this the model predictive controller is designed and tuned by using model predictive control designer toolbox in MATLAB.

1.4. Scope

The scope is limited to design the fuzzy model predictive controller for the biomass boiler using the measured data gathered from industry. And the biomass boiler system is limited from the biomass heat generation to steam output. This work only considers the measured variables that are found in waterside of the biomass boiler.

1.5. Significance of the study

This work deals with the modeling of Biomass Boiler using fuzzy modeling and controlling of it by linear model predictive control after the linearization of the fuzzy model. Fuzzy modeling can approximate the nonlinear plant to linear one and can express it as linear parameter varying system. This have great significance for sugar factories to model the boiler which is nonlinear. Model predictive control also has great advantage in highly coupled and MIMO systems, since it can handle coupling and constraints. It can also minimize energy by using constraints. To avoid the extravagance of the resources and control loss of interactions in the boiler plant of sugar factory MPC is an efficient control strategy. This work shows the modeling and control of the biomass boiler.

1.6. Thesis organization

This thesis consists of a total of five chapters and it is organized as follows.

Chapter two presents the theoretical overview of biomass boiler, parts of biomass boiler and advantage of biomass boiler and review of related works. Chapter three discuses about the development of the model of biomass boiler using system identification and the mechanism of linearization. It also focuses on designing of model predictive control and tuning mechanism of it to get good performance.

Chapter four discusses the results and simulation results for the proposed controller.

Chapter five summarizes the major issues discussed throughout this paper and finally draws the general conclusions. And also this chapter indicates the future work by some recommendations.

Chapter Two

2. Theoretical background and Literature review

2.1. Introduction

Boiler is a steam generator that uses combustion as its main heat source to convert water to steam for a wide range of industrial purposes such as power generation, chemical processes and heating. The process is continuous and large scale. A typical medium sized boiler generates 30,000 kg of steam per hour, at a temperature of 420^{o}c and a pressure of 4.5 MPa. A very large scale electric utility boiler may generate more than 4,000,000 kg of steam per hour. A boiler is comprised of two basic systems. The one is steam water system also called the water side of the boiler in which water is introduced and heated by transference through the water tubes and converted to steam, then it leaves the system.

The other boiler system is the fuel air-flue gas system also referred as the fire side of the boiler. This system provides the heat which is transferred to the water. The inputs for this system are the fuel and air which is required to burn the fuel. The outputs for this system are flue gas and ash [6]. A simple schematic diagram representation of a typical boiler system is shown in figure 2.1.

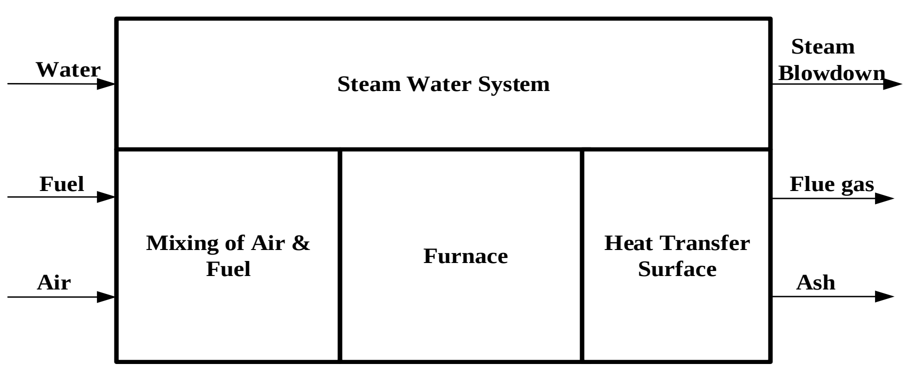

Fig. 2-1: Basic diagram of boiler.

2.2. Boiler components

Furnace

The combustion chamber/furnace releases the heat and hence it can be considered as the heat transfer system. There are three important parameters that are required for combustion to take place in the furnace; these are time, temperature and turbulence.

Fans

A boiler consists of induced draft /ID/ fan and forced draft/FD/ fan. The ID fan pulls the air through the boiler producing a negative pressure in the furnace. The FD fan pushes the air for combustion through the boiler.

Wind box

Used to distributes secondary air to the burners. The wind box may have damper adjustments to create turbulence to improve combustion.

Flue Gas Heat Exchangers

Used for reducing heat loss in the boiler flue gases, to improve boiler efficiency and to recover and to cool the flue gases. Since the flue gas temperature is higher than the air temperature, heat is transferred from the flue gas to the combustion air via the convection heat transfer surface of the combustion air preheater.

Combustion Air Preheater

Is one type of heat exchanger. As the flue gas leaves the boiler, it passes through the combustion air preheater. The combustion air passes through the air preheater heat exchanger before being mixed with the fuel. Since the temperature of flue gas is higher than air temperature, heat is transferred from the flue gas to combustion air via the convection heat transfer surface of the combustion air preheater. This transfer of heat cools the flue gas and thus reduces its heat loss and reduces the temperature of the air to the sack, while the added heat in the combustion air entering the furnace enhance the combustion process. This reduces the fuel requirements in an amount equal in heat value to the amount of heat that has been transferred in the combustion air preheater, thus improving efficiency.

Economizer

The economizer heats the feed water to improve boiler efficiency and reduce heat loss to the stack. The increased heat in the feed water reduces the boilers requirement for fuel and combustion air. The flue gas leaves the boiler and enters economizer where it makes contact with the heat transfer surface, in the form of water tubes, through which the boiler feed water flows. Since the flue gas is at high temperature than the water, the flue gas is cooled and the water temperature is increased. Cooling the flue gas reduces its heat loss in an amount equal to the increased heat in the feed water to the boiler.

Attemperator (Desuperheater):

Is one of the component of the boiler which is used to reduce the steam temperature to appoint which is still above the saturation point. It adjusts the temperature of steam by pumping a fine spray of comparatively cool water droplets into the vapor.

Super heater

The super heater provides additional heat to the steam to remove any moisture from the steam, thereby improving the quality of the steam. The dryness of the steam is the determining factor of its quality.

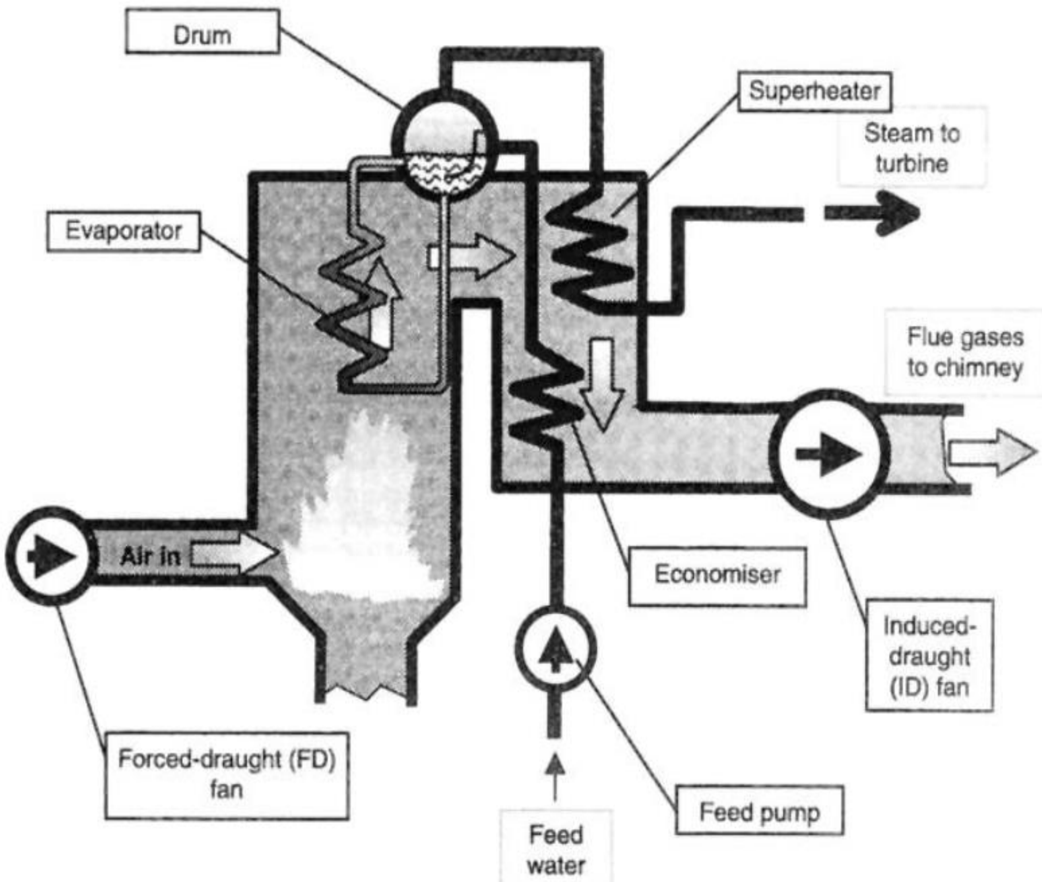

Fig. 2-2: Schematic of Boiler[34]

Boiler Drums

Boilers may consist of an upper drum, or steam or water drum, and a lower drum, or mud drum. The mud drum terminology comes from the function of the lower drum. Although the water is treated to eliminate dissolved solids, some solids always remain in the water.

These solids collected in the lower drum, and a drum blowdown is required to remove the solids that collect in the lower drum. The blowdown may be manual or automatic [6].

2.3. Types of model used for boiler control

The development of a success boiler control strategy is largely dependent on the availability of a good boiler model. The models described in the reviewed literatures can be classified in to two groups.

1. White box (first principle models): these models are derived by using the laws of mass and energy transfer. It uses a physical parameter such as volume and mass which may be obtained directly from the biomass boiler plant [18]. This type of model can be considered as generic biomass boiler model which may be capable to represent different biomass boiler plant. First principle models require a considerable development effort and may involve a large computational overhead [42].
2. Data based models of biomass boiler which are generated from plant data using system identification technique. This type of model has an advantage that may be generated more quickly than first principle models and may even be generated online. However, they are not generic [42]. This type of modeling is usually a trial and error process where parameters are estimated by considering different structures and selecting the one that achieves best fitting between real and estimated data. ARX (Auto-Regressive model with Exogenous input) model is the simplest model used in the literature [12].

2.4. Control Mechanism of Biomass Boiler

The boiler control system is defined by two design decisions.

1. Configuration of the control system: This is specified by the choice of manipulated and controlled variables. The control system can be configured as single input single output, multi input single output, single input multi output and multi input multi output.
2. Choice of control methodology: there are many control strategies for boiler control [7]. The following control methodologies have been investigated in the reviewed literatures.
    a. PID control
    b. Predictive control
    c. Model reference adaptive control
    d. Multivariable control

PID control: a conventional boiler control scheme is described in boiler control systems engineering, which describes control of drum water level, steam pressure and steam temperature. Each variable is controlled using a SISO controller. Drum level is controlled as SISO system by using PI controller which uses feed water as a manipulating variable. The comparative studies of PID and MPC controllers for boiler drum level control is presented in [8].

Predictive control: there has been a recent surge of interest in the application of predictive methodologies to boiler control due to the suitability of it for many types of control problems. The predictive control strategy is based on the use of an explicit model to predict the process future behavior. This control strategy also uses the cost function which is quadratic function of set-point tracking error [5]. It can be applied to multivariable control problems, self-tuning or adaptive control schemes, nonlinear control schemes and constrained control schemes [7]. To solve the coupling and nonlinearities' in small scale bio fired boiler model based control strategy was implemented [9].

Model Reference Adaptive control: it has strong immunity for the disturbance and the varying of system parameters [8]. Fuzzy adaptive PID control theory is a new theory that combine traditional PID with fuzzy logic which does not require the exact mathematical model of controlled object and adapt to the fast, small overshoot and the short transition [10].

2.5. Review of Related Works

There are different types of Boiler control mechanisms suggested by different researchers. Some of the researches which are concerned with the controllers like adaptive fuzzy, multivariable control, PI (proportional integral), DCS (distributed control system) and Model fuzzy predictive controller are reviewed.

Grate firing is a state of the art technique that is currently used in biomass combustion for heat and power production. Now a day's grate fired boilers are well designed and sufficiently equipped with monitoring systems. However, usage of modern control strategies for biomass combustion is still not very wide spread [1].

Robust multivariable PI controller using $H\infty$ loop-shaping techniques is designed for boiler system control [12]. Electrical boiler control using PLC (programmable logic controller) and DCS (distributed control system) is designed [14]. Robust control of boiler system with linear time invariant(LTI) model is presented [13].

Robust decentralized controller design for bench mark PID (proportional integral derivative) problem is presented in [14]. Both model based and model free methods in the controller design was carried out on an experimental small-scale water heating boiler firing wood chips of various quality was presented [15]. Viktor Placek and Bohumil Sulc presented Biomass Boiler control design by modeling. They study the effect of model free and model based control strategy and effect of them on the control of Biomass Boiler [15]. M.Tothoka and J. Dubjak presented application of computational intelligence in Biomass combustion control in Medium Scale Boilers. They study only the water temperature control and adjustment of primary and secondary air flows according to trends of carbon monoxide emissions [16].

Choosak and Amut presented steam generating prediction of a biomass boiler using artificial neural network. They study the application of an intelligence technique, to deal with the variation of biomass materials that affects to the biomass boiler efficiency [17]. Control systems of existing Biomass Boilers usually combine typical PID (proportional integral derivative) feedback control which is executed by programmable logic controller and personal control functioning as operator control panel.

Henryk Rusinowski presented mathematical modeling of Biomass fired fluidized bed Boiler. The research studied the model which is dependent on composition and uses system identification for identifying unknown parameters by linear regression. The limitation of this study is that it only presented the dynamic model and it doesn’t consider the pressure and temperature [18].

Markus, Reiter, Brunner, Dourdoumal and Ingwald presented Model based control of a small-scale Biomass Boiler. But they focus on the furnace part of the boiler, because they design the controller for the flue gas oxygen content and heat flow in the bio grate boiler [9].

Predictive control system based on type Takagi-Sugeno fuzzy model was developed for a polymerization process which is a highly nonlinear dynamic process [21]. Model predictive control is designed based on the dynamic model which describes mass transfer between the pasta and surrounding air for controlling of pasta drying process [23].

Model predictive Fuzzy control is designed for a steam boiler system based on the gathered data from the selected plant [27]. Linear quadratic control theory was applied to design the control laws for the boiler drum pressure and level control [33].

Shiji, Anish and Swapna studied boiler drum level control in thermal power plant. They had present the comparative studies of PID and Model reference adaptive control for boiler drum level control. This work showed that MRAC (Model reference adaptive control) has comparatively less overshoot than PID and much faster settling occurs for it, but they considered only one measured variable [8].

Ahmed and Ali studied the control of boiler water temperature using model reference adaptive control. They had shown this control strategy has strong immunity for the disturbance and the varying of system parameters. However, this study didn't show the manipulated variables and it considers only one controlled variable [41].

As mentioned above the researchers mainly done their project on coal fired and fossil fuel fired boilers. Studies on biomass boilers are highly limited while, many biomass boilers use traditional controlling mechanism. The current control mechanism such as adaptive control and PI controllers are not efficient and accurate controllers for nonlinear and multivariable systems like biomass boiler. Because these controllers require decoupling of MIMO systems into SISO system. However, decoupling has a problem of losing interactions between variables. While, PLC can control MIMO systems but, it cannot predict the future behavior of the system and it is difficult to find errors. Also hold up time is indefinite when a problem is occurred. Therefore, this thesis work proposes development of a control system for the biomass boiler by using fuzzy model predictive controller.

Chapter Three

3. System Modeling and Controller Design

3.1. Introduction

In this chapter the fuzzy modeling of biomass boiler and model predictive controller will be discussed. It shows different modeling paradigms, algorithms and procedures which can apply for identification of nonlinear system. The model of biomass boiler is generated from the input output data which is gathered from Wenji-Shoa sugar factory by using black box modeling approach.

3.2. Modeling and identification of biomass boiler

This thesis work used fuzzy identification method for the modeling of Biomass Boiler. The first step for the system identification is choosing the input and output signals from the system to be modeled. This paper uses 4 inputs (Water flow, Fuel flow, Airflow1 and Air flow2) and 3 outputs (Drum pressure, Steam temperature and Drum level). Because these variables are critical for the steam generation due to the following reasons.

Pressure control: Steam is used in a large number of industrial applications. The most applications are the process heating and driving the steam turbines to generate electricity. Boiler will typically work at high pressure; as low-pressure operation will result in carryover of water. High pressure steam has lower specific volume, which will allow pipes to carry less weight. However most of the applications will require some parameter control.

Steam Temperature control: The steam turbine or the process plant which receive the steam usually requires the temperature to remain at a precise value over the entire load range, and also different bank of tubes are affected in different ways by the radiation from the burners and the flow of hot gases, an additional requirement is to provide some means of adjusting the temperature of the steam with in different parts of the circuit, to prevent any section from becoming over heated. To get best possible heat rate to reduce fuel costs the temperature should be maintained at the rated value [37].

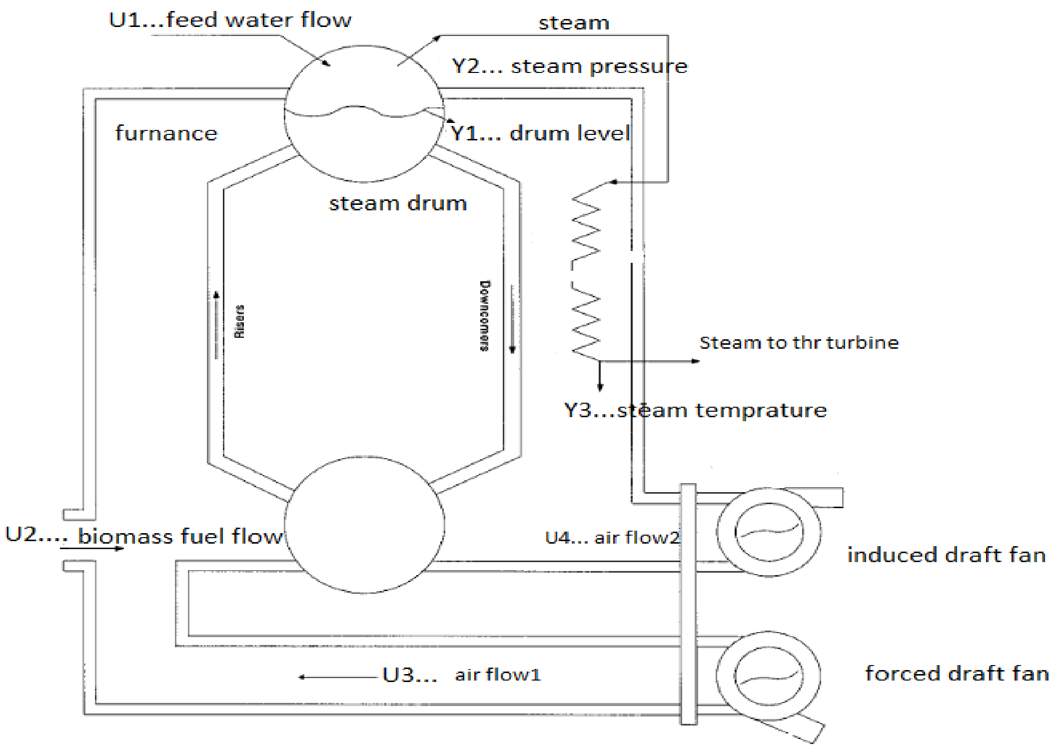

Fig. 3-1: Input output description of biomass boiler [13]

Drum level control: The drum level must be controlled to the limits specified by the boiler manufacturer. Because if the level exceeds the limit boiler water carryover into the super heater or the turbine may occur leading to damage and resulting in extensive maintenance costs or outages of either the turbine or the boiler. On the other hand, if the level is low over heating of the water wall tubes may cause tube ruptures and serious accidents, resulting in expensive repairs, down time and injury or death to personnel. When the level gets too low the boiler will trip to prevent damage to the tubes and cracks in the tubes where they connect to the boiler drum [36].

The model should not be either simple or complex. If the model is too simple, it cannot properly represent the studied characteristics of the system and does not serve its purpose. However, the model should not be too complex if it is to be practically useful [35].

There are different modeling paradigms.

1. White box modeling (physical, mechanistic, first principle modeling): it requires a knowledge or understanding of the systems nature and behavior, and of a suitable mathematical treatment that leads to a usable model.
2. Black box modeling: in this type of modeling the structure of the model is hardly related to the structure of the real system. The identification problem consists of estimating the parameters in the model. If representative process data is available black box models usually can be developed quite easily without requiring process specific knowledge.
3. Gray box modeling: it combines white box and black box modeling, such that the known part of the systems is modeled using physical knowledge, and the unknown or less certain parts are approximated in a black box manner, using process data and black box modeling structures with suitable approximation properties.

A common drawback of most standard modeling approaches is that they cannot make effective use of extra information, such as the knowledge and experience of engineers and operators, which is often imprecise and qualitative in its nature. Fuzzy modeling and control are typical examples of techniques that make use of human knowledge and deductive processes [35].

3.2.1. Fuzzy modeling

Fuzzy modeling is type of modeling method which describe relationships between variables by means of if-then rules. Fuzzy models integrate the logical processing of information with attractive mathematical properties of general function approximators. It can also make effective use of data driven learning algorithms and can be combined with conventional regression techniques. There are three types of fuzzy model.

1. Linguistic fuzzy models (Mamdani model): in this type of model both the antecedent and the consequent are fuzzy propositions. The general form is:

   If $X\ is\ A_i$ then $Y\ is\ B_{i,}\ i = 1,2,3, \dots, K$

   Where X is the antecedent variable, which represents the input to the fuzzy system, and Y is the consequent variables representing the output of the fuzzy system. A_i and B_i are linguistic terms (fuzzy sets) defined by multivariate membership functions μ_{Ai} and μ_{Bi} respectively and K denotes the number of rules in the model.
2. Fuzzy relational models: it encodes associations between linguistic terms defined in the system's input and output domains by using fuzzy relations. The individual elements of the relation represent the strength of association between the fuzzy sets. As an example, assume a static model with single input $x \in X$ and single out put $y \in Y$.

$$A = \{A_1, A_2, A_3, \dots, A_m\}$$

$$B = \{B_1, B_2, B_3, \dots, B_m\}$$

The crisp output of the fuzzy relational model output is calculated using the weighted mean:

$$y_0 = \frac{\sum_{j=1}^{N} \mu_j b_j}{\sum_{j=1}^{N} \mu_j} \tag{3.1}$$

3. Takagi-Sugeno Models:

A fuzzy rule based model which is suitable for the approximation of a large class of nonlinear systems was introduced by Takagi and Sugeno. In this model the rule consequents are crisp functions of the model inputs.

$$R_i: \boldsymbol{if}\ x\ is\ A_i\ \boldsymbol{then}\ y_i = f_i(x),\ \ i = 1,2,\ldots,k,$$

Where $x \in R^p$is the input (antecedent) variable and $y_i \in R$ is the output(consequent) variable. R_i denotes the i^{ih} rule, and K is the number of rules in the rule base. A_i is the antecedent fuzzy set of the i^{ih} rule, defined by a multivariate membership function:

$\mu_{Ai}(x): R^p \to [0,1]$.

As in the linguistic model, the antecedent proposition is usually expressed as a logical combination of simple propositions with univariate fuzzy sets defined for the individual components of x, often in the conjunctive form:

$$R_i: if\ x_1\ is\ A_{i1}\ and\ x_2 is\ A_{i2}\ and \ldots\ x_p\ is\ A_{ip}\ \ then\ y_i = \ f_i(x), i = 1,2,\ldots,k,$$

The consequent functions are typically chosen as instance of a suitable parametrized function, whose structure remains equal in all the rules and only the parameters vary. A simple and practically useful parametrization is the affine linear form:

$$y_i = a_i^T x + b_i \tag{3.2}$$

Where a_i is a parameter vector and b_i is a scalar offset.

Among these fuzzy modeling mechanisms Takagi-Sugeno fuzzy model is implemented for biomass boiler, since it shows the functional relation between the inputs and the outputs of the given system which is suitable for control design and it can handle the approximation of highly nonlinear systems.

3.2.2. Inference in the TS model

Before the output can be inferred, the degree of fulfillment of the antecedent denoted $\beta_i(x)$ must be computed. It is computed as a combination of the membership degrees of the individual propositions using the fuzzy logic operators.

In the Takagi Sugeno model, the inference is reduced to a simple algebraic expression, similar to the fuzzy-mean defuzzification formula.

$$y = \frac{\sum_{i=1}^{K} \beta_i(x) y_i}{\sum_{i=1}^{K} \beta_i(x)} \tag{3.3}$$

The normalized degree of fulfillment

$\lambda_i(x) = \frac{\beta_i(x)}{\sum_{j=1}^{K} \beta_i(x)}$, the affine TS model with a common consequent structure can be expressed as a pseudo linear model with input dependent parameters:

$$y = \left(\sum_{i=1}^{K} \lambda_i(x) a_i^T\right) x + \sum_{i=1}^{K} \lambda_i(x) b_i = a^T(x)x + b(x) \tag{3.4}$$

The parameters $a(x), b(x)$ are convex linear combinations of the consequent parameters a_i and b_i i.e.:

$$a(x) = \sum_{i=1}^{K} \lambda_i(x) a_i \,, \quad b(x) = \sum_{i=1}^{K} \lambda_i(x) b_i \tag{3.5}$$

Depending on these parameters and the input and output delays the fuzzy model can be described as discrete model of the system and also methods can be developed to design controllers with desired closed loop characteristics and to analyze their stability [35].

3.2.3. Fuzzy Identification

Fuzzy identification is a technique and algorithms for constructing fuzzy models from data. An effective approach to the identification of complex nonlinear systems is to partition the available data into subsets and approximate each subset by a simple model [11]. Since biomass boiler is a highly nonlinear and highly interacted system it is difficult to model by using physical equations. Due to this reason this work has used system identification tool for modelling of biomass boiler.

Fuzzy clustering can be used as a tool to obtain a partitioning of data where the transitions between the subsets are gradual rather than abrupt. Clustering techniques are among the unsupervised (learning) methods, since they do not use prior class identifiers. Clustering techniques can be applied to data that is quantitative (numerical), qualitative (categoric), or a mixture of both. In this work the clustering of quantitative data is considered. The data are collected from Wenji-Shoa sugar factory biomass boiler plant. Each observation consists of 7 measured variables grouped in to 7-dimensional column vector:

$$z = [z_{1k} \; z_{2k} \ldots \; z_{7k}\,]^T \,, z_k \in R^{200}$$

A set of 200 observation is conducted and is represented as 200×7 matrix:

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{17} \\ \vdots & \ddots & \vdots \\ z_{2001} & \cdots & z_{2007} \end{bmatrix}$$

Table 3-1: Specification of the Biomass Boiler in Wenji-Shoa sugar factory

Generated Electric Power	31.5 Mw
Amount of steam generated	130 ton/hour
Amount of feed water	170 ton/hour
Feed water temperature	110 ^{0}c
Steam temperature	505 ^{0}c
Steam Pressure	65 PSI

The rows of Z contains the samples of time and the columns are physical variables observed in the system (water flow, air flow, fuel flow (stoker feed velocity), steam pressure, drum level and steam temperature). The clustering method which is used in this work is product space fuzzy clustering. It able to decompose a nonlinear identification problem into a set of locally linear models.

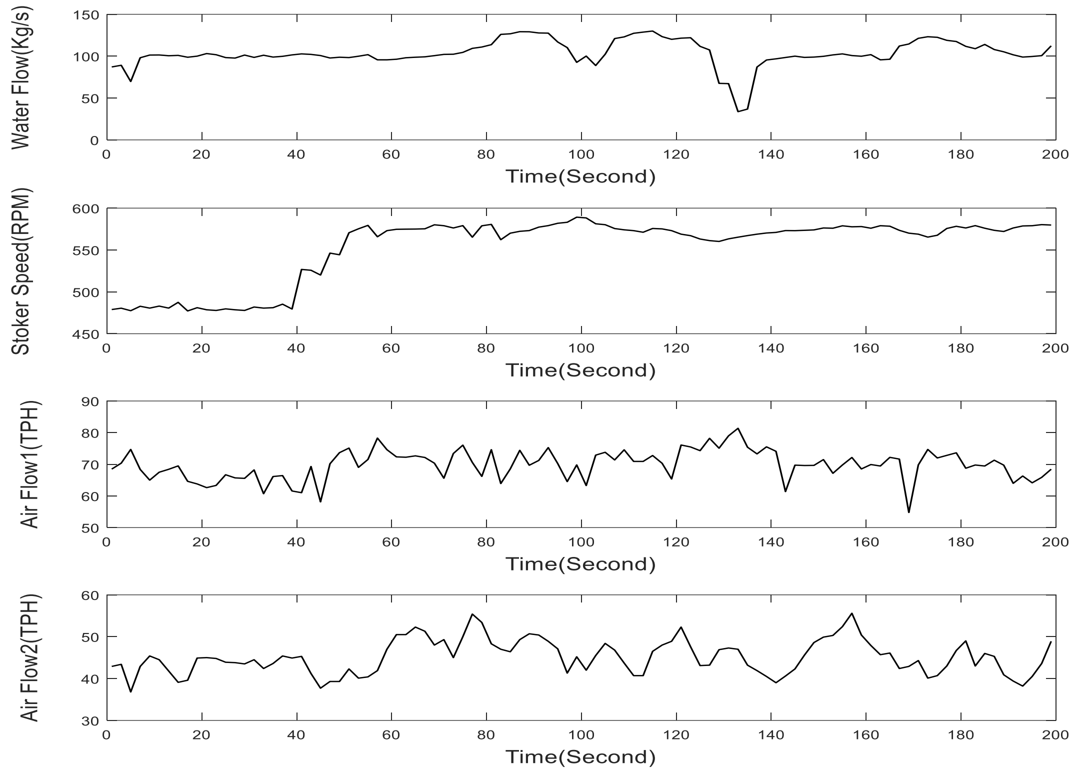

Fig. 3-2: Data plot for input of identification data

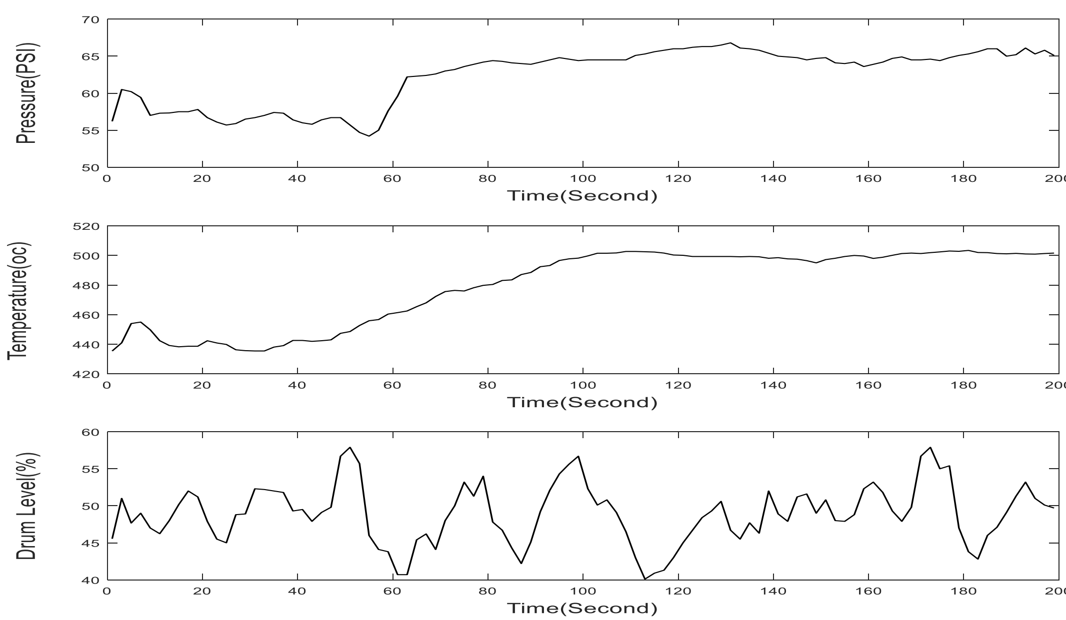

Fig. 3-3: Data plot for output of identification data

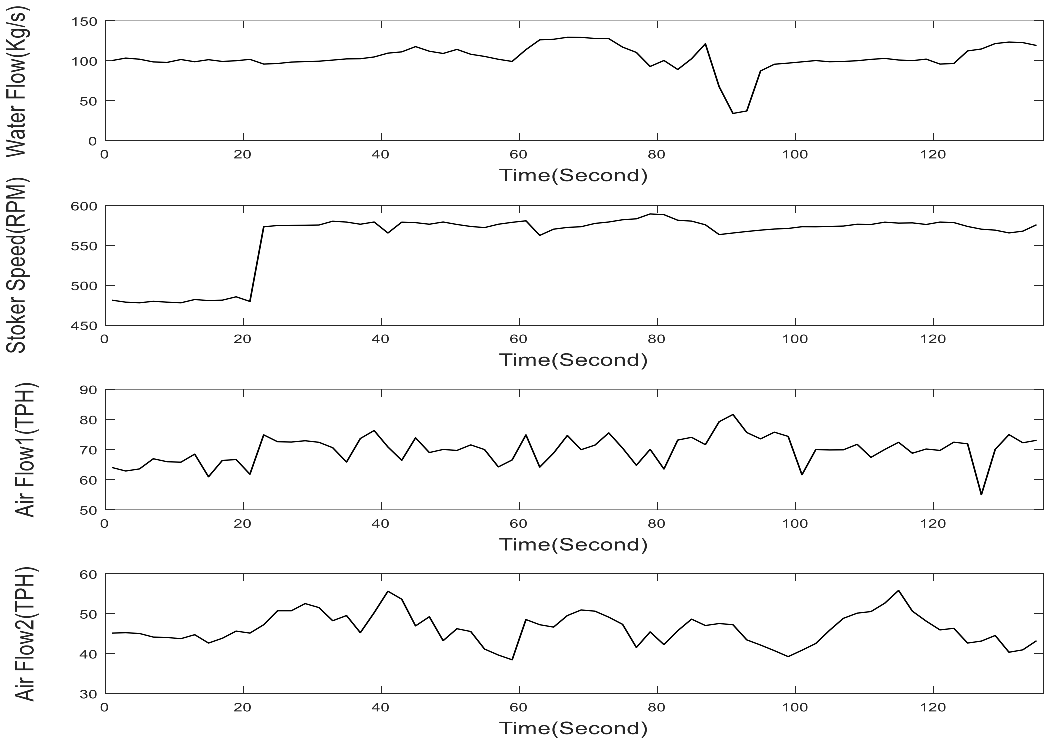

Fig. 3-4: Data plot for input of validation data

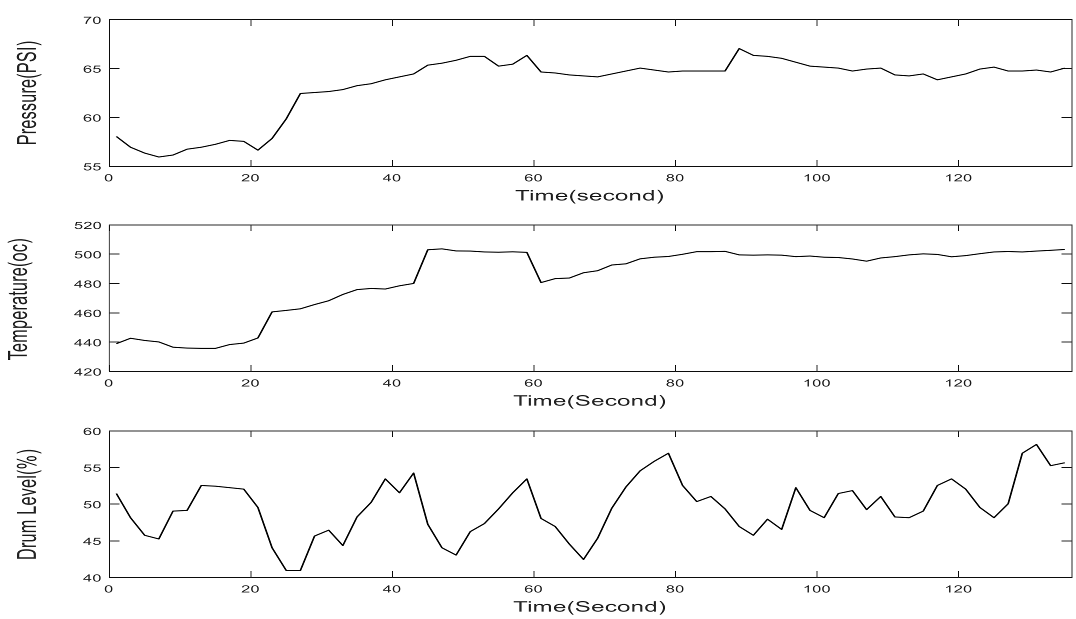

Fig. 3-5: Data plot for output of validation data

Steps of the identification procedure

1. Design of identification experiments and data collection: this is an important initial step for any identification method, since it determines the information content of the identification data set. The data should be multi-sinusoidal signal or a step-wise signal with random amplitude and random width.
2. Structure selection: the purpose of this step is to determine the relevant input and output variables with respect to the aim of the modeling exercise. In the identification of dynamic systems, the structure and the order of the system model should be chosen by the user, based on the prior knowledge about the process.
3. Clustering of the data: the location and the parameters of the sub models are found by clustering the available data into hyper planar or hyper ellipsoidal clusters. Each the clusters defines a fuzzy region in which the system can be approximated locally by a linear submodel.

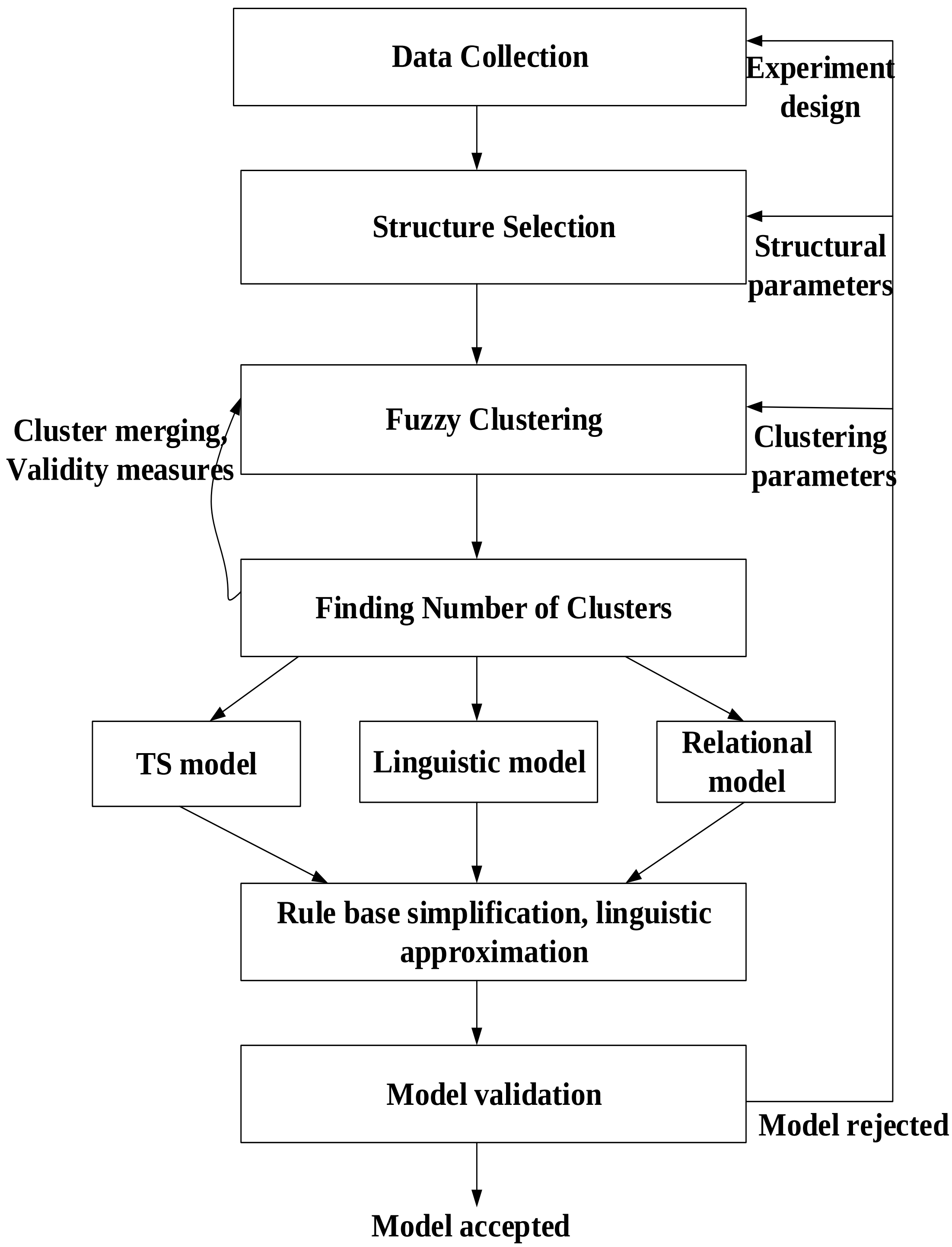

Fig. 3-6: Fuzzy Identification procedure

4. Selection of the number of clusters: by applying cluster validity measures, compatible cluster merging, or a combination of the two techniques, an appropriate number of clusters can be found.
5. Generation of an initial fuzzy model: fuzzy clustering divides the available data into groups in which local linear relations exists between the inputs and the output. In order to obtain a model suitable for prediction or controller design, a rule based fuzzy model of a selected structure is derivated from the available fuzzy partition and from the cluster prototypes.
6. Simplification and reduction of the initial model:
7. Model validation: by means of validation, the final model is either accepted as appropriate for the given purpose, or it is rejected. In addition to the usual numerical validation by means of simulation, interpretation of fuzzy models plays an important role in the validation step. The coverage of the input space by the rules can be analyzed and for an incomplete rule base, additional rule can be provided based on prior knowledge, local linearization or first principle models [35].

For the modeling of biomass boiler, the Input-output Black-box Model is selected. Among these black box models the NARX (Nonlinear Autoregressive with exogenous input) model is frequently used with many nonlinear identification method, such as neural networks, radial basis functions and fuzzy models.

The NARX model establishes a relation between the past input-output data and the predicted output:

$$y(k+1) = F\left(y(k), \dots, y\left(k - n_y + 1\right), u(k), \dots, u(k - n_u + 1)\right), \tag{3.6}$$

Where k denotes discrete time samples, n_u and n_y are integers related to the system's order, and F denotes a fuzzy model. In the NARX model, the regression vector is a collection of a finite number of past inputs and outputs,

$$x(k) = [y(k), \dots, y(k - n_y + 1), u(k), \dots, u(k - n_u + 1)]^T \tag{3.7}$$

The regressand is the predicted output $y(k + 1)$. Hence from a set of observed inputs and outputs of the boiler system $S = \{(u(ij), y(ij)) | i = 1,2, \dots ,200 \;\&\; j = 1, 2, \dots 7\}$, the model can be approximated by using static nonlinear regression. Delays from the input to the output can be directly incorporated in the regression vector.

$x(k) = [y(k), \dots, y(k - n_y + 1), u(k - n_d + 1), \dots, u(k - n_d - n_u + 2)]^T$, where n_d is the delay in samples usually take it as 1 for simplicity. Since Biomass Boiler is MIMO system, it can be represented in two ways: the function F should be a vector-valued function, or it should be decomposed into a set of coupled MISO systems. There are different algorithms used for identification by product space clustering method [34]. Among these this work uses Gustafson-Kessel algorithm for identification due to the following reasons.

1. The size of clusters is limited by the definitions of distance measure. The fuzzy sets induced by the partition matrix are compact, have typically one distinct extreme, and hence are easy to interpret.
2. In comparison with other algorithms the GK algorithm is relatively insensitive to the initialization of the partition matrix (cluster prototypes)
3. As the GK algorithm is based on an adaptive distance measure, it is not so sensitive to scaling (normalization, standardization) of the data.

4. The GK algorithm can detect clusters of different shapes, not only linear subspaces.

3.2.4. Gustafson-Kessel Algorithm

Gustafson and Kessel extended the standard fuzzy c-means algorithm by employing an adaptive distance norm, in order to detect clusters of different geometrical shapes in one data set [35]. Each cluster has its own norm-inducing matrix A_i, which yields the following inner product form:

$$D_{ikA_i}^2 = (Z_K - V_i)^T A_i (Z_K - V_i) \tag{3.8}$$

The matrices A_i are used as optimization variable in the c-means functional, thus allowing each cluster to adapt the distance norm to the local topological structure of the data.

The objective function of the GK algorithm is defined by:

$$J(Z; U, V, A) = \sum_{i=1}^{c} \sum_{k=1}^{N} (\mu_{ik})^m D_{ikA_i}^2 \tag{3.9}$$

Where $U \in M_{fc}, V \in R^{n \times c}$ and $m > 1$. The solutions,

$$(U, V, A) = \underbrace{\arg min}_{M_{fc} \times R^{n \times c} \times PD^n} \quad J(Z; U, V, A) \tag{3.10}$$

are stationary points of J, where PD^n denotes a space of $n \times n$ positive definite matrices.

$$A_i = [\rho_i \det(F_i)]^{1/n} F_i^{-1} \tag{3.11}$$

where F_i is the fuzzy covariance matrix of the i^{th} cluster defined by:

$$F_i = \frac{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m (Z_K - V_i^l)(Z_K - V_i^l)^T}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m} \tag{3.12}$$

Steps for GK algorithm computing

Given the data set Z, choose the number of clusters $1 < c < N$, the weighting exponent $m > 1$ and the termination tolerance $\varepsilon > 0$. Initialize the partition matrix randomly, such that

$U^{(0)} \in M_{fc}$ repeat for $l = 1,2,\dots$

$step$ 1: Compute cluster prototypes (means:)

$$V_i^{(l)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(l-1)})^m} \qquad 1 \le i \le c \tag{3.13}$$

$step$ 2: $Compute\ the\ cluster\ covariance\ matrices$:

$$F_i = \frac{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m (Z_K - V_i^l)(Z_K - V_i^l)^T}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m}, \qquad 1 \le i \le c \tag{3.14}$$

$step$ 3: $Compute\ the\ distances$:

$$D_{ikA_i}^2 = (Z_K - V_i^{(l)})^T [\rho_i \det(F_i)]^{1/n} F_i^{-1} (Z_K - V_i^{(l)}), 1 \le i \le c, 1 \le k \le N. \tag{3.15}$$

$step$ 4: $Update\ the\ patition\ matrix$:

If $D_{ikA_i} > 0\ for\ \ 1 \le i \le c,\ 1 \le k \le N,$

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{c} \left(D_{ikA_i} / D_{jkA_i} \right)^{2/(m-1)}} \tag{3.16}$$

Otherwise

$$\mu_{ik}^{(l)} = 0\ if\ D_{ikA_i} > 0\ , and\ \mu_{ik}^{(l)} \in [0,1]\ with\ \sum_{i=1}^{c} \mu_{ik}^{(l)} = 1.$$

Until $\left\|U^{(l)} - U^{(l-1)}\right\| < \varepsilon$.

An advantage of the GK algorithm over FCM is that GK algorithm can detect clusters of different shape and orientation in one data set.

By using the product space clustering method with GK algorithms the Takagi Sugeno fuzzy model of Biomass Boiler is expressed in appendix section.

3.2.5. Linearization of Takagi-Sugeno model

At each sample time, the local A and B matrices are calculated as follows: Calculate the degree of fulfillment $\omega_i\big(x(k)\big)$ of the antecedents, using product as the fuzzy logic and operator [22]. The rule inference gives:

$$y_l(k+1) = \frac{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).\, y_{li}(k+1)}{\sum_{i=1}^{k} \omega_{li}(x_l(k))} \tag{3.17}$$

$$y_{li}(k+1) = (a_{li} y(k) + b_{li} u(k) + \theta_{li}) \tag{3.18}$$

Define $\hat{a}\ and\ \hat{b}$ as:

$$\hat{a} = \frac{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).a_{li}}{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big)} \quad , \quad \hat{b} = \frac{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big).b_{li}}{\sum_{i=1}^{k} \omega_{li}\big(x_l(k)\big)}$$

Define $x, u\ and\ y$ for the state-space description as:

$$x(k) = [x_1(k), x_1(k-1), \dots, x_1\big(k - n_{yl}\big), \dots, x_{n0}(k), x_{n0}(k-1), \dots, x_{n0}\big(k - n_{yn0}\big)]^T$$

$$u(k) = [u_1(k - n_{d1} + 1), \dots, u_1(k - n_{di}), u_{ni}\left(-n_{d_{ni}}\right), \dots, u_{ni}\Big(k - n_{d_{ni}} - n_{u_{ni}} + 1\Big)]^T$$

$$y(k) = [x_1(k), x_2(k), \dots, x_{n0}(k)]^T \tag{3.19}$$

The local linear system matrices are now derived as follows:

A is a $\sum_{j=1}^{n0} n_{yj} \times \sum_{j=1}^{n0} n_{yj} (= \alpha_1)$ matrix

$$A = \begin{bmatrix} \hat{a}_{11} & \hat{a}_{12} & \cdots & \cdots & \cdots & \cdots & \hat{a}_{1\alpha_1} \\ 1 & 0 & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & 1 & \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ \hat{a}_{21} & \hat{a}_{22} & \dots & \cdots & \cdots & \cdots & \hat{a}_{2\alpha_1} \\ 0 & \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \hat{a}_{n01} & \hat{a}_{no2} & \dots & \cdots & \cdots & \cdots & \hat{a}_{n0\alpha_1} \\ 0 & \cdots & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \cdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 1 & 0 \end{bmatrix}$$

$B\ is\ a\ \sum_{j=1}^{n0} n_{uj} \times \sum_{j=1}^{ni} n_{uj} (= \alpha_2)$ matrix:

$$B = \begin{bmatrix} \hat{b}_{11} & \hat{b}_{12} & \dots & \hat{b}_{1\alpha_2} \\ 0 & \dots & \dots & 0 \\ \vdots & \dots & \dots & \vdots \\ 0 & \dots & \dots & 0 \\ \hat{b}_{21} & \hat{b}_{22} & \dots & \hat{b}_{2\alpha_2} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{b}_{n01} & \hat{b}_{n02} & \dots & \hat{b}_{no\alpha_2} \\ \vdots & \ddots & \ddots & \vdots \end{bmatrix} \tag{3.20}$$

and $C$is a $n_0 \times \sum_{j=1}^{no} n_{yj}$ matrix:

$$C = \begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\ 0 & \cdots & \cdots & 1 & \cdots & 0 \end{bmatrix}$$

The ones in C are positioned such that $y_l(K) = x_l(k)$ [31].

After determining the average weight for each rule the global linearized discrete time model of the Biomass Boiler is obtained. This obtained model can be described by state space representation and discrete time transfer function. These models are presented as follows.

The locally linearized state space model of the Biomass Boiler is:

$$A = \begin{bmatrix} 0.9003 & -0.0314 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.8364 & -0.0934 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ -0.9681 & 0 & -0.0238 & 0 & 0.7763 & -0.2087 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} -0.0303 & 0.0539 & 0.0033 & 0.0105 & -0.0032 & 0.0142 & 0.0056 & 0.0026 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.0598 & -0.0885 & 0.0788 & -0.0044 & 0.075 & -0.038 & 0.0048 & 0.0824 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -0.1388 & 0.1043 & -0.1769 & 0.1588 & -0.1402 & 0.0072 & 0.1689 & 0.0345 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$E = \begin{bmatrix} -3.8597 \\ 25.883 \\ 110.5241 \end{bmatrix} \tag{3.21}$$

After global linearization of the obtained fuzzy model the discrete time model of the biomass boiler is obtained. The continuous time transfer function of the biomass boiler can be obtained by using MATLAB by converting the discrete time model obtained from Takagi Sugeno fuzzy model.

The transfer function representation is described as follows:

$$\begin{pmatrix} P(z) \\ T(z) \\ L(z) \end{pmatrix} = \begin{pmatrix} G_{11} & G_{12} & G_{13} & G_{14} \\ G_{21} & G_{22} & G_{23} & G_{24} \\ G_{31} & G_{32} & G_{33} & G_{34} \end{pmatrix} \begin{pmatrix} U_1(z) \\ U_2(z) \\ U_3(z) \\ U_4(z) \end{pmatrix} + \begin{pmatrix} G_{15} \\ G_{25} \\ G_{35} \end{pmatrix} \tag{3.22}$$

But the drum level is affected by the other two outputs and the effect of them is described as transfer function in the following section.

where

$P(z)$ is Drum pressure

$T(z)$ is Steam Temperature

$L(z)$ is Drum Level and

$U_1(z)$ is Water flow $\quad$ $U_3(z)$ is Air flow1

$U_2(z)$ is Fuel flow $\quad$ $U_4(z)$ is Air flow2

$$G_{11} = \frac{-0.0302z + 0.0539}{z^2 + 0.9003z - 0.0314} \qquad G_{12} = \frac{0.0033z + 0.0105}{z^2 + 0.9003z - 0.0314}$$

$$G_{13} = \frac{-0.0032z + 0.0142}{z^2 + 0.9003z - 0.0314} \qquad G_{14} = \frac{0.0056z + 0.0026}{z^2 + 0.9003z - 0.0314}$$

$$G_{21} = \frac{0.0598z - 0.0885}{z^2 + 0.8364z - 0.0934} \qquad G_{22} = \frac{0.0788z - 0.0044}{z^2 + 0.8364z - 0.0934}$$

$$G_{23} = \frac{0.075z - 0.038}{z^2 + 0.8364z - 0.0934} \qquad G_{24} = \frac{0.0048z + 0.0824}{z^2 + 0.8364z - 0.0934}$$

$$G_{31} = \frac{-0.1388z + 0.1043}{z^2 - 0.7763z + 0.2087} \qquad G_{32} = \frac{-0.1769z + 0.1588}{z^2 - 0.7763z + 0.2087}$$

$$G_{33} = \frac{-0.1402z + 0.0072}{z^2 - 0.7763z + 0.2087} \qquad G_{34} = \frac{0.1689z + 0.0345}{z^2 - 0.7763z + 0.2087}$$

$$G_{15} = \frac{-3.8597z^2}{z^2 + 0.9003z - 0.0314} \qquad \frac{L(s)}{P(s)} = \frac{-0.9681z}{z^2 - 0.7763z + 0.2087}$$

$$G_{25} = \frac{25.88z^2}{z^2 + 0.8364z - 0.0934} \qquad \frac{L(s)}{T(s)} = \frac{-0.0238z}{z^2 - 0.7763z + 0.2087}$$

$$G_{35} = \frac{110.5241z^2}{z^2 - 0.7763z + 0.2087}$$

3.3. Model Predictive Control Design

Model predictive control(MPC) is a class of control techniques first derived from internal model control(IMC) and is widely applied in the process industries due to its capability to deal with constraints in an optimal fashion; as the name suggests MPC is based on predictions of set point tracking behavior or disturbance rejection over both past controlled and manipulated variables measurement, in which each prediction is followed by an optimization routine to find the optimal input for the closed loop response imposed by a certain criteria, such as maximizing a profit function or production rate [29].

MPC calculations are performed at each sampling time which can be also set by the control designer; these calculations are based on current measurements and predictions of future output values. Two types of computation are primordial in a MPC controller: set point calculation and control calculations which includes process constraints and other parameters that are able to be manually specified. The main task of a MPC controller is to determine a sequence of control moves in the manipulated variable, so the system can be tracked to its set point in an optimal fashion [24].

MPC controllers are widely applied in process industries due to its capability to deal in an optimal form with input/output process constraints (upper and lower values for specific variable); in this sense, one should be able to safely operate the system by restricting it to be conducted in a limited region of operation, such as a maximum opening degree in a valve.

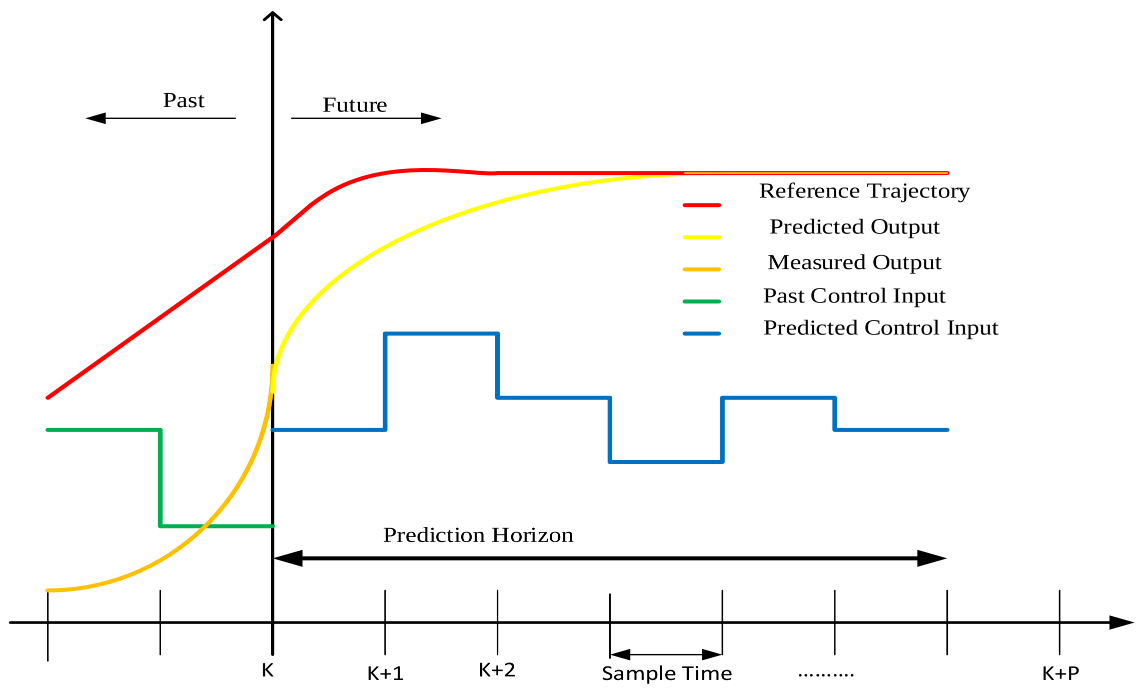

Fig. 3-7: Basic concept of MPC

The control calculations are based on minimizing the predicted deviations from the reference trajectory. When using MPC, an optimization problem is solved at each time step k through an objective function based on output predictions over a prediction horizon of P time steps; this objective function is minimized by a selection of manipulated variables moves over a control horizon of M control moves [29]. Generally, model predictive control is one of the most researched synthesis approaches which, based on a model of a process, computes the best control strategy according to a set of predefined goals over a future time horizon. In fact, this is one of the most distinguishable feature of MPC. While, traditional control systems determine the course of actions based on the evolution of the error of previous iterations, MPC is driven by evaluating the expected future error due to a chosen control trajectory in a receding horizon fashion.

3.3.1. Principle of model predictive control

At each consecutive iteration of the algorithm $k, k = 1,2,3, \ldots$, the whole vector of the future values of the manipulated variable

$$u(k) = \begin{bmatrix} u(k/k) \\ \vdots \\ u(k+M-1/k) \end{bmatrix}$$ is calculated on-line.

$u(k+p|k\ )$ denotes the value of manipulated variable for the sampling instant $k+p$ calculated at the current iteration, M is the control horizon. And the vector of increments of the future values of the manipulated variable.

$$\Delta u(k) = \begin{bmatrix} \Delta u(k|k) \\ \vdots \\ \Delta u(k+M-1|k) \end{bmatrix}$$ can be determined.

Where $$\Delta u(k+p|k) = \begin{cases} u(k|k) - u(k-1) & if\ p = 0 \\ u(k+p|k) - u(k+p-1|k) & if\ p \geq 1 \end{cases} \qquad (3.23)$$

The vector of these two decision variables $u(k)$ and $\Delta u(k)$ is successively found on-line as a result of solving an optimization problem. The minimized objective (cost) function usually consists of two parts. The first one is the difference between the predicted trajectory of the output variable and the set point trajectory (the predicted control errors) over the prediction horizon N. The second part is rate of change of inputs over the control horizon M. The role of the second part is to reduce excessive change of the manipulated variables. The cost function is:

$$J(k) = \sum_{p=1}^{N} (y^{sp}(k+p|k) - \hat{y}(k+p|k))^2 Q + \sum_{p=0}^{M-1} (\Delta u(k+p|k))^2 R \qquad (3.24)$$

where $Q\&R > 0$ are a weighting coefficients (the greater its value, the lower the increments of the manipulated variable and, hence, the slower control).

$y^{sp}(k+p|k)$ is the set point value at sampling instant of $k+p$.

$\hat{y}(k+p|k)$ is the predicted value of the output variable at time instant of $k+p$.

Consecutive output predictions, for the whole prediction horizon, i.e. for $p = 1,2, \dots, N$ are calculated by means of a dynamic model of the process. It is assumed that

$u(k+p|k) = u(k+M-1|k)$ for $P = M, \dots, N$ (it means that $\Delta u(k+M|k) = \cdots = \Delta u(k+N|k) = 0$).

There are three common important features of all MPC algorithms: the receding horizon, successive on-line optimization of the cost function and the direct use of a dynamic model of the process for prediction calculation. Unlike the classical control algorithms, e.g. the PID controller, not only the current value of the manipulated variables is calculated, but the whole future control policy. The model predictive control algorithm is able to find the future control sequence which gives good control accuracy.

3.3.2. Main components of Model Predictive Control

1. Dependence of actions on predictions

   PID controller doesn't consider the future implementation while model predictive control do. Prediction is invaluable for avoiding otherwise unforeseen disasters.

2. Predictions are based on a model: the model must show the dependence of the output on the current measurement variable and the current/future inputs. A model is used to generate system predictions. One should use the simplest model which is fit for purpose, that gives accurate enough predictions.

3. Selecting the current input: the predicted inputs are selected as those minimizing a given cost function. The cost function should be as simple as one can get away with for the desired performance.
4. Receding horizon: the receding horizon should be greater than the system settling time. The horizon selected for predictions should include all significant dynamics (for instance use the settling time) otherwise performance may be poor and important events may be unobserved.
5. Optimal or safe performance: we can only control as precisely as we can model; if we want a highly tuned controller we need a very accurate model.
6. Tuning: model predictive control will always give stable control (at least for the nominal) so the important judgements are how to get a balance between input activity, balance between the performance in different loops, good sensitivity and speed of the response. For the achievement of these balances tuning of weighting matrices are very important. Tuning is often straight forward if one can define the relative importance of performance in different loops.
7. Constraint handling: constraints are very much dependent on the control algorithms. The algorithm selected will depend upon many variables (i.e. related to potential increase in profit) and sampling time. MPC takes systematic accounts of constraints and hence allows better performance.
8. Systematic use of future demands: MPC gives systematic feedforward design which integrated with the constraint handling.

9. Systematic control design for multivariable systems: MPC algorithms can deal with multivariable (MIMO) systems in a systematic way. It allows systematic design for MIMO systems [10].

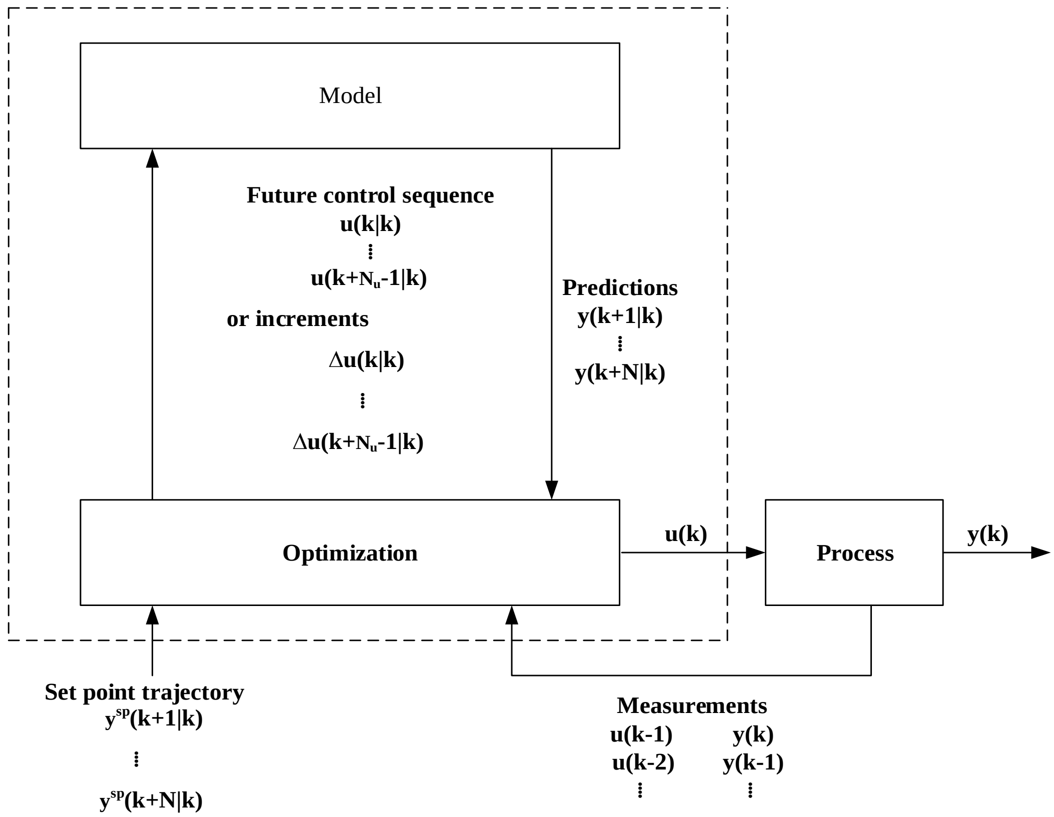

Fig. 3-8: The general structure of the MPC algorithm

3.4. Model Predictive Control Algorithms

There are many algorithms for Model predictive control. Among these algorithms this work uses Generalized predictive control. Because it shows good performance and a certain degree of robustness with respect to over parameterization or poorly known delays. It also can handle many different control problems for a wide range of plants with a reasonable number of design variables, which have to be specified by the user depending upon a prior knowledge of the plant and control objectives.

The basic idea of GPC is to calculate a sequence of future control signals in a such a way that it minimizes a multistage cost function defined over a prediction horizon. The index to be optimized is the expectation of a quadratic function measuring the distance between the predicted system output and some predicted reference sequence over the horizon plus a quadratic function measuring the control effect [41].

Generalized predictive control has many ideas in common with the other predictive controllers. It provides an analytical solution (in the absence of constraints), it can deal with unstable and non-minimum phase plants and incorporates the concept of control horizon as well as the consideration of weighting of control increments in the cost function [35]. Other type of MPC algorithms are subsets or limiting case of GPC, due to this reason this work uses it for the controlling of Biomass Boiler.

3.4.1. Formulation of General Predictive Control

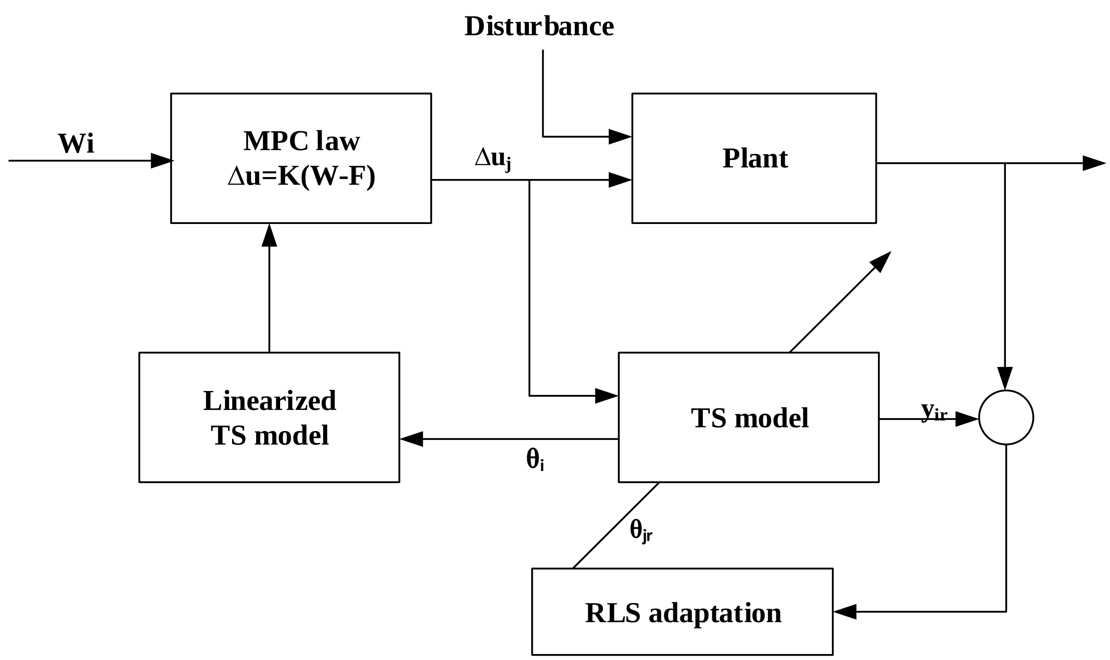

Fig. 3-9: Fuzzy MPC structure

For many industrial applications in which disturbances are non-stationary an integrated Controller Auto-Regressive Moving-Average (CARIMA) model is more appropriate [31]. Since Biomass Boiler is MIMO system and has non-stationary disturbance CARIMA model is suitable for it. A CARIMA model for multi input multi output process is given by:

$$A(z^{-1})y(t) = B(z^{-1})u(t-1) + \frac{1}{\Delta}C(z^{-1})e(t) \tag{3.25}$$

Where $A(z^{-1})$ and $C(z^{-1})$ are $n \times n$ monic polynomial matrices and $B(z^{-1})$ is an $n \times m$ polynomial matrix defined as:

$$A(z^{-1}) = I_{n\times n} + A_1 z^{-1} + A_2 z^{-2} + \cdots + A_{n_a} z^{-n_a}$$

$$B(z^{-1}) = B_0 + B_1 z^{-1} + B_2 z^{-2} + \cdots + B_{n_b} z^{-n_b}$$

$$C(z^{-1}) = I_{n\times n} + C_1 z^{-1} + C_2 z^{-2} + \cdots + C_{n_c} z^{-n_c}$$

Where

$\Delta = 1 - z^{-1}$

$y(t)$ is $n \times 1$ output vector

$u(t)$ is $m \times 1$ input vector

$e(t)$ is $n \times 1$ noise vector at time t.

The cost function of the GPC is given by:

$$J(N_1, N_2, N_3) = \sum_{j=P_0}^{P} \left|\left|\hat{y}(t+j|t) - w(t+j|t)\right|\right|_Q^2 + \sum_{j=1}^{M} \left|\left|\Delta u(t+j-1)\right|\right|_R^2 \tag{3.26}$$

Where $\hat{y}(t+j|t)$ is an optimum j-step ahead prediction of the system output on data up to time t; that is the expected value of the output vector at time t if the past input and output vectors and the future control sequence are known. P_0 and P are the minimum and maximum prediction horizons, M is control horizon and $w(t+j)$ is a future setpoint or reference sequence for the output vector. R and Q are positive definite weighting matrices.

Consider the matrix $C(z^{-1}) = I_{n\times n}$ [41]. Because this matrix is difficult to estimate with sufficient accuracy in practice, especially in the multivariable case. The optimal prediction for the output vector can be generated as in the monovariable case as follows:

Consider the Diophantine equation:

$$I_{n\times n} = E_j(z^{-1})\tilde{A}(z^{-1}) + z^{-j}F_j(z^{-1}) \tag{3.27}$$

Where $\tilde{A}(z^{-1}) = A(z^{-1})\Delta, E_j(z^{-1})$ and $F_j(z^{-1})$ are unique polynomial matrices of order $j-1$ and n_a respectively.

If the system equation 3.3 is multiplied by $\Delta E_j(z^{-1})$:

$$E_j(z^{-1})\tilde{A}(z^{-1})y(t+j) = E_j(z^{-1})B(z^{-1})\Delta u(t+j-1) + E_j(z^{-1})e(t+j) \tag{3.28}$$

After some manipulation:

$$y(t+j) = F_j(z^{-1})y(t) + E_j(z^{-1})B(z^{-1})\Delta u(t+j-1) + E_j(z^{-1})e(t+j) \tag{3.29}$$

Notice that because the degree of $E_j(z^{-1})$ is $j-1$, the noise term of the above equation are all in the future. By taking the expectation operator and considering that $E[e(t)] = 0$, the expected value for $y(t+j)$ is given by:

$$\hat{y}(t+j|t) = F_j(z^{-1})y(t) + E_j(z^{-1})B(z^{-1})\Delta u(t+j-1) \tag{3.30}$$

Add $E_j(z^{-1})E[e(t)]$ to prediction $\hat{y}(t+j|t)$ to extend the prediction to nonzero mean noise.

3.4.2. Recursion of the Diophantine Equation

Consider as the solution $(E_j(z^{-1}), F_j(z^{-1}))$ for the Diophantine equation has been obtained [41]. That is:

$$I_{n\times n} = E_j(z^{-1})\tilde{A}(z^{-1}) + z^{-j}F_j(z^{-1}) \tag{3.31}$$

with

$$\tilde{A}(z^{-1}) = A(z^{-1}\Delta) = I_{n\times n} + \hat{A}_1 z^{-1} + \hat{A}_2 z^{-2} + \cdots + \hat{A}_{n_a} z^{-n_a} + \hat{A}_{n_a+1} z^{-(n_a+1)}$$

$$E_j(z^{-1}) = E_{j,0} + E_{j,1}z^{-1} + E_{j,2}z^{-2} + \cdots + E_{j,j-1}z^{j-2}$$

$$F_j(z^{-1}) = F_{j,0} + F_{j,1}z^{-1} + F_{j,2}z^{-2} + \cdots + F_{j,n_a}z^{-n_a}$$

Now consider the Diophantine equation corresponding to the prediction for $\hat{y}(t+j+1|t)$.

$$I_{n\times n} = E_{j+1}(z^{-1})\tilde{A}(z^{-1}) + z^{-(j+1)}F_{j+1}(z^{-1}) \tag{3.32}$$

Subtract 3.9 from 3.10

$$0_{n\times n} = \left(E_{j+1}(z^{-1}) - E_j(z^{-1})\right)\tilde{A}(z^{-1}) + z^{-j}\left(z^{-1}F_{j+1}(z^{-1}) - F_j(z^{-1})\right) \tag{3.33}$$

Matrix $\left(E_{j+1}(z^{-1}) - E_j(z^{-1})\right)$ is of degree j. Let us make

$$\left(E_{j+1}(z^{-1}) - E_j(z^{-1})\right) = \hat{R}(z^{-1}) + R_j z^{-j} \tag{3.34}$$

Where $\hat{R}(z^{-1})$ is an $n \times n$ polynomial matrix of degree smaller or equal to $j-1$ and R_j is an $n \times n$ real matrix. By substituting

$$0_{n\times n} = \hat{R}(z^{-1})\tilde{A}(z^{-1}) + z^{-j}\left(R_j\tilde{A}(z^{-1}) + z^{-1}F_{j+1}(z^{-1}) - F_j(z^{-1})\right) \tag{3.35}$$

As $\tilde{A}(z^{-1})$ is monic, it is easy to see that $\hat{R}(z^{-1}) = 0_{n\times n}$. That is, matrix $E_{j+1}(z^{-1})$ can be computed recursively by:

$$E_{j+1}(z^{-1}) = E_j\left(z^{-j}\right) + R_j z^{-j} \tag{3.36}$$

The following expression can be obtained from equation 3.13

$$R_j = F_{j,0}$$

$$F_{j+1,i} = F_{j,i+1} - R_j\tilde{A}_{i+1}\ for\ i = 0, \dots, \delta(F_{j+1})$$

It can easily be seen that the initial conditions for the recursion equation are given by:

$$E_1 = I, F_1 = z\left(I - \tilde{A}\right) \tag{3.37}$$

By making the polynomial matrix $E_j(z^{-1})B(z^{-1}) = G_j(z^{-1}) + z^{-j}G_{jp}(z^{-1})$,with $\delta\left(G_j(z^{-1})\right) < j$, the prediction equation can now be written as:

$$\hat{y}(t+j|t) = G_j(z^{-1})\Delta u(t+j-1) + G_{jp}(z^{-1})\Delta u(t-1) + F_j(z^{-1})y(t) \tag{3.38}$$

Notice that the last two terms of the right-hand side of the above equation depend on past values of the process outputs and input variables, while the first term only depends on future values of the control signal. That is the response obtained when the initial conditions are zero [41].

$y(t-j) = 0, \Delta u(t-j) = 0\ for\ j = 0,1,2, \dots$ the above equation can be written as

$$\hat{y}(t+j|t) = G_j(z^{-1})\Delta u(t+j-1) + f_j \tag{3.39}$$

With $f_j = G_{jp}(z^{-1})\Delta u(t-1) + F_j(z^{-1})y(t)$.

Let us now consider a set of N j-ahead predictions:

$$\hat{y}(t+1|t) = G_1(z^{-1})\Delta u(t) + f_1$$

$$\hat{y}(t+2|t) = G_2(z^{-1})\Delta u(t+1) + f_2 \tag{3.40}$$

$$\vdots$$

$$\hat{y}(t+N|t) = G_N(z^{-1})\Delta u(t+N-1) + f_N$$

Because the recursive properties of the E_j polynomial matrix described above, can be written as:

$$\begin{bmatrix} \hat{y}(t+1|t) \\ \hat{y}(t+2|t) \\ \vdots \\ \hat{y}(t+j|t) \\ \vdots \\ \hat{y}(t+N|t) \end{bmatrix} = \begin{bmatrix} G_0 & 0 & \dots & 0 & \dots & 0 \\ G_1 & G_0 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ G_{j-1} & G_{j-2} & \dots & G_0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ G_{N-1} & G_{N-2} & \dots & \dots & \dots & G_0 \end{bmatrix} \begin{bmatrix} \Delta u(t) \\ \Delta u(t+1) \\ \vdots \\ \Delta u(t+j-1) \\ \vdots \\ \Delta u(t+N-1) \end{bmatrix} + \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_j \\ \vdots \\ f_N \end{bmatrix} \tag{3.41}$$

Where $\mathrm{G_j}(\mathrm{z}^{-1}) = \sum_{\mathrm{i=0}}^{\mathrm{j-1}} \mathrm{G_i} \mathrm{z}^{-(\mathrm{N-j+i})}$. The prediction can be expressed as:

$$y = Gu + f \tag{3.42}$$

The first row of matrix G can be calculated as the step response of the plant when a unit step is applied to the first control signal. Row i can be obtained in a similar manner by applying a unit step to the i-input. In general, matrix G_k can be obtained as:

$$(G_k)_{i,j} = y_{i,j}(t+k+1) \tag{3.43}$$

Where $(G_k)_{i,j}$ is the (i,j) element of matrix G_k and $y_{i,j}(t+k+1)$ is the i-output of the system when a unit step has been applied to control input j at time t. The prediction matrices (G_j, G_{jp}, F_i) for 36 prediction horizon are obtained by using MATLAB, but it is difficult to present here.

The free response term can be calculated recursively by:

$$f_{j+1} = z\left(I - \tilde{A}(z^{-1})\right)f_j + B(z^{-1})\Delta u(t+j) \tag{3.44}$$

with $f_0 = y(t)\ and\ \Delta u(t+j) = 0\ for\ j \geq 0$.

The control signal is kept constant after the first M control moves, the set of predictions affecting the cost function given by

$$y_{P_0P} = G_{P_0PM}u_M + f_P \tag{3.45}$$

Where $u_M = [\Delta u(t)^T \dots \Delta u(t+M-1)^T]^T, f_{P_0P} = [f_{P_0}^T \dots f_P^T]^T$ and G_{P_0PM} is the following submatrix of G

$$G_{P_0PM} = \begin{bmatrix} G_{P_0-1} & G_{P_0-2} & \dots & G_{P_0-P} \\ G_{P_0} & G_{P_0-1} & \dots & G_{P_0+1-M} \\ \vdots & \ddots & \ddots & \vdots \\ G_{P-1} & G_{P-2} & \dots & G_{P-M} \end{bmatrix} \tag{3.46}$$

With $G_i = 0 for\ i < 0$. The cost function can be written as:

$$J = \left(G_{P_0PM}u_M + f_{P_0P} - w\right)^T \bar{Q}\left(G_{P_0PM}u_M + f_{P_0P} - w\right) + u_M^T\bar{R}u_M \tag{3.47}$$

Where $\bar{R} = diag(R, \dots, R)$ and $\bar{Q} = diag(Q, \dots, Q)$ if there are no constraints, by minimizing equation 3.25 the optimal control input can be expressed as:

$$\Delta u(t+k-1) = \left(G_{P_0PM}^T\bar{Q}G_{P_0PM} + \bar{R}\right)^{-1}G_{P_0PM}^T\bar{Q}\left(w - f_{P_0P}\right) \tag{3.48}$$

Because of the receding control strategy, only $\Delta u(t)$ is needed at instant t. Thus only the first m rows of $\left(G_{P_0PM}^T \bar{Q} G_{P_0PM} + \bar{R}\right)^{-1} G_{P_0PM}^T \bar{Q}$, say K, have to be computed. This can be done beforehand for the non-adaptive case. The control law can then be expressed as $\Delta u(t) = K(w - f)$. That is a linear gain matrix that multiplies the predicted errors between the predicted references and the predicted free response of the plant [37].

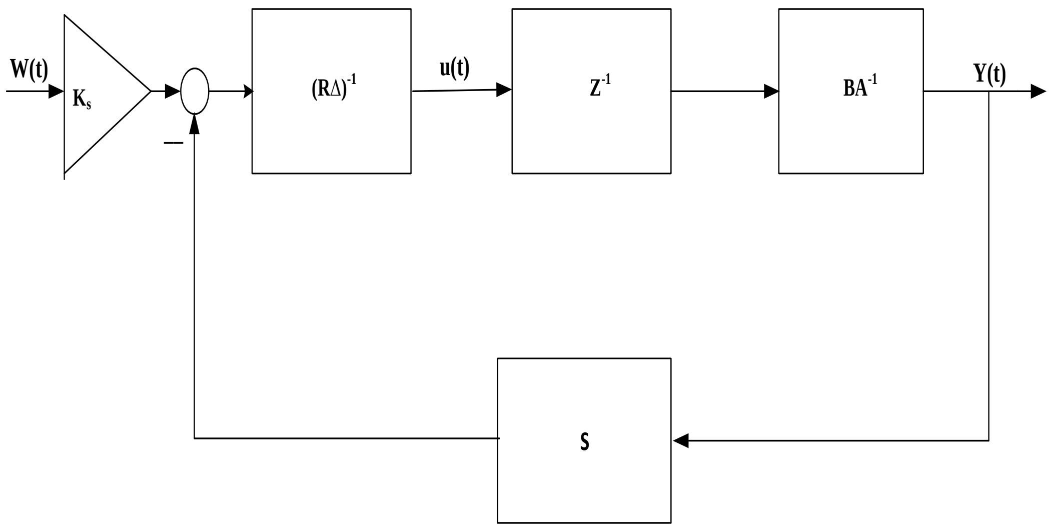

Fig. 3-10: MPC analysis as a closed-loop control scheme

As described above the optimal control input is expressed by minimizing the above cost function given as follows.

$$\Delta u(t+k-1) =$$

$$\left(G_{P_0PM}^T \bar{R} G_{P_0PM} + \bar{Q}\right)^{-1} G_{P_0PM}^T \bar{R}.\left[w(t+k) - G_{jp}(z^{-1})\Delta u(t-1) - F_j(z^{-1})y(t)\right] \qquad (3.49)$$

For the biomass boiler since it is 4×3 MIMO system, the control signal becomes:

$$\begin{bmatrix}\Delta u_1(t)\\ \Delta u_2(t)\\ \Delta u_3(t)\\ \Delta u_4(t)\end{bmatrix} = \underbrace{\begin{bmatrix}k_{s,11} & k_{s,12} & k_{s,13}\\ k_{s,21} & k_{s,22} & k_{s,23}\\ k_{s,31} & k_{s,32} & k_{s,33}\\ k_{s,41} & k_{s,42} & k_{s,43}\end{bmatrix}}_{k_s}\begin{bmatrix}w_1(t)\\ w_2(t)\\ w_3(t)\end{bmatrix} - \underbrace{\underbrace{\begin{bmatrix}k_{11} & \cdots & k_{1(2n)}\\ k_{21} & \cdots & k_{2(2n)}\\ k_{31} & \cdots & k_{3(2n)}\\ k_{41} & \cdots & k_{4(2n)}\end{bmatrix}}_{k_0}\begin{bmatrix}G_{11}\\ G_{21}\\ \vdots\\ G_{jp}\end{bmatrix}}_{R_1(z^{-1})}\begin{bmatrix}\Delta u_1(t-1)\\ \Delta u_2(t-1)\\ \Delta u_3(t-1)\\ \Delta u_4(t-1)\end{bmatrix} -$$

$$\underbrace{\begin{bmatrix}k_{11} & \cdots & k_{1(2n)}\\ k_{21} & \cdots & k_{2(2n)}\\ k_{31} & \cdots & k_{3(2n)}\\ k_{41} & \cdots & k_{4(2n)}\end{bmatrix}\begin{bmatrix}F_1\\ F_2\\ \vdots\\ F_j\end{bmatrix}}_{S(z^{-1})}\begin{bmatrix}y_1(t)\\ y_2(t)\\ y_3(t)\end{bmatrix} \qquad (3.50)$$

Where $n = P - P_0 + 1, k_0 \in K(1 \dots 4, 1 \dots 2n), k_{s,11} = k_{11} + k_{13} + \cdots + k_{1(2n-1),}$ and similarly the other elements of k_s can be determined as linear combinations of elements of k_0 [37].

After reduction of the above block a closed-loop form of MPC results:

$$R(z^{-1})\Delta u(t) = k_s w - S(z^{-1})y(t); \quad R = I + R_1 \qquad (3.51)$$

From globally linearized model of the Biomass Boiler the integrated controller exogenous auto regressive moving average model can also be obtained.

For the Biomass Boiler the CARIMA model parameters are given as follows.

$$A(z^{-1}) =$$

$$\begin{bmatrix}1 + 0.9003z^{-1} - 0.0314z^{-2} & 0 & 0\\ 0 & 1 + 0.8364z^{-1} - 0.0934z^{-2} & 0\\ -0.9681z^{-1} & -0.0238z^{-1} & 1 - 0.7763z^{-1} + 0.2087z^{-2}\end{bmatrix}$$

$$B(z^{-1}) =$$

$$\begin{bmatrix}-0.0302z^{-1} + 0.0539z^{-2} & 0.0033z^{-1} + 0.0105z^{-2} & -0.0032z^{-1} + 0.0142z^{-2} & 0.0056z^{-1} + 0.0026z^{-2}\\ 0.0598z^{z^{-1}} - 0.0885z^{-2} & 0.0788z^{-1} - 0.0044z^{-2} & 0.075z^{-1} - 0.038z^{-2} & 0.0048z^{-1} + 0.0824z^{-2}\\ -0.1388z^{-1} + 0.1043z^{-2} & -0.1769z^{-1} + 0.1588z^{-2} & -0.1402z^{-1} + 0.0072z^{-2} & 0.1689z^{-1} + 0.0345z^{-2}\end{bmatrix}$$

$$\frac{C(z^{-1})}{\Delta}e(t) = \begin{bmatrix} -3.8597 & 0 & 0 \\ 0 & 25.883 & 0 \\ 0 & 0 & 110.5241 \end{bmatrix} \quad (3.52)$$

And the polynomial $\hat{A}(z^{-1})$ can be calculated as:

$$\hat{A}(z^{-1}) = A(z^{-1}).\Delta$$

3.5. Tuning of Model Predictive Control

Model Predictive Control algorithms possess several design parameters such as the prediction horizon, control horizon and the penalty weights in the objective function. To get best performance these parameters should be tuned as a desired manner. There are many literatures which are done on the tuning mechanisms of model predictive control. Depending on these literatures this work also deals with the tuning mechanism of the parameters of MPC which can minimize the objective function and achieve the desired performance. Since there is no general rule for the tuning of MPC parameters this work uses manual tuning method and some rules from the literatures. The tuning parameters are the minimum and maximum prediction horizons (P_0&P), the control horizon (M), the model horizon (N), the sampling time (t_s), controlled variable weight (Q) and rate of change of inputs weight (R) [29].

- ❖ Maximum and minimum prediction Horizons (P_0&P): they mark the limits of the time in which it is desirable for the output to follow the reference. If minimum prediction horizon is high, it is unimportant if there are errors in the first instants which will stimulate a smooth response of the process. P_0 should not less than the dead time of the process. Mostly P_0 is taken as one. The maximum prediction horizon is selected as t_{90}/T_s or maximum $(N + M)$ (infinite) as much possible to ensure the closed loop system stable. Where t_{90} is the time which the response reaches 90% of its steady state response, T_s is sampling time, $N\&M$ are model and control horizons respectively [39].

- ❖ Control horizon (M): M specifies the degree of freedom in selecting future controls. After M future samples Δu are considered as zero. For unstable system the value of M should be at least equal to the number of unstable poles in the plant, but for stable plants the value of M can be chosen as 1. For general case M can be chosen as $1 < M < P$.
- ❖ Model horizon (N): it affects the conditions of the state matrix A. As a model horizon increases matrix A becomes more ill-conditioned. It is selected as $30 < N < 120$.
- ❖ Controlled variables weight (Q): it is possible to achieve tighter control of a particular measured output by selectively increasing the relative weighting element.
- ❖ Rate of change of inputs weight (R): the role of R is to penalize excessive incremental control actions. The larger value of R, the more sluggish the control will become. If the system is expressed in state space representation; the output penalty matrices for strictly proper system can be given by

$$Q = C^T C \text{ and } 0 < R < 1 \text{ [38].}$$

Depending on these mechanisms model predictive control parameters can be tuned. In this work the parameters are tuned based on the above mechanisms and by using trial and error method. In trial and error method, one can adjust these parameters by seeing the closed loop response of the Biomass Boiler until the desired response is obtained.

In this work the tuned parameters of Model Predictive Controller for Biomass Boiler are given as in the following manner.

$T_s = 1sec$, $N = 31$, $M = 5$, $P_0 = 1$, $P = 36$ and the penalty matrices Q and R are gives as follows: $R = \begin{bmatrix} 0.0202 & 0 & 0 & 0 \\ 0 & 0.0202 & 0 & 0 \\ 0 & 0 & 0.0202 & 0 \\ 0 & 0 & 0 & 0.0202 \end{bmatrix}$

$$Q = \begin{bmatrix} 1.95 & 0 & 0 \\ 0 & 1.95 & 0 \\ 0 & 0 & 1.95 \end{bmatrix}$$

Chapter Four

4. Result and Discussion

4.1. Introduction

This chapter states about the overall SIMULINK blocks of biomass boiler, all simulation results with brief discussion and analysis. The simulation results and discussions include the result of biomass boiler without controller (open loop response) and with model predictive controller. The results which are obtained from this work are compared with previous works done by other researchers. The biomass boiler is a 4×3 MIMO system, but it can be controlled as three MISO systems or one MIMO system. This is shown in simulation results which are presented in the next section of this chapter.

Firstly, the system identification model validation result will be presented. Secondly, the response of each output will be presented. In the second part of simulation; first a simulation result for open loop system without any controller is discussed. Next the result of the biomass boiler with the model predictive controller is presented and finally the comparisons of the results are discussed in brief.

4.2. Model validation for system identification

The system identification is performed by using FMID (fuzzy modeling and identification) toolbox developed by Robert Babuska. This tool box is integrated with MATLAB to identify the system model. The model is validated by variance accounted for (VAF) between two signals. The VAF of two equal signals is 100%. The VAF index is used to evaluate the quality of a model, by comparing the true output with the output of the model. VAF can be expressed mathematically as follows:

$$VAF = 100\%.\left[1 - \frac{var(y_1 - y_2)}{var(y_1)}\right] \quad 4.1$$

Where, y_1 is validation data of the system and

y_2 is the identified model output

The model identification uses some parameters which are selected and tuned by the user depending on the performance that needed by the user. For the biomass boiler model identification, the following parameters are used.

$$N_y = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 1 & 1 & 2 \end{bmatrix}$$

$$N_u = \begin{bmatrix} 2 & 2 & 2 & 2 \\ 2 & 2 & 2 & 2 \\ 2 & 2 & 2 & 2 \end{bmatrix}$$

$$N_d = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

Where N_y is number of delays in output

N_u is number of delays in input

N_d is number of transport delays

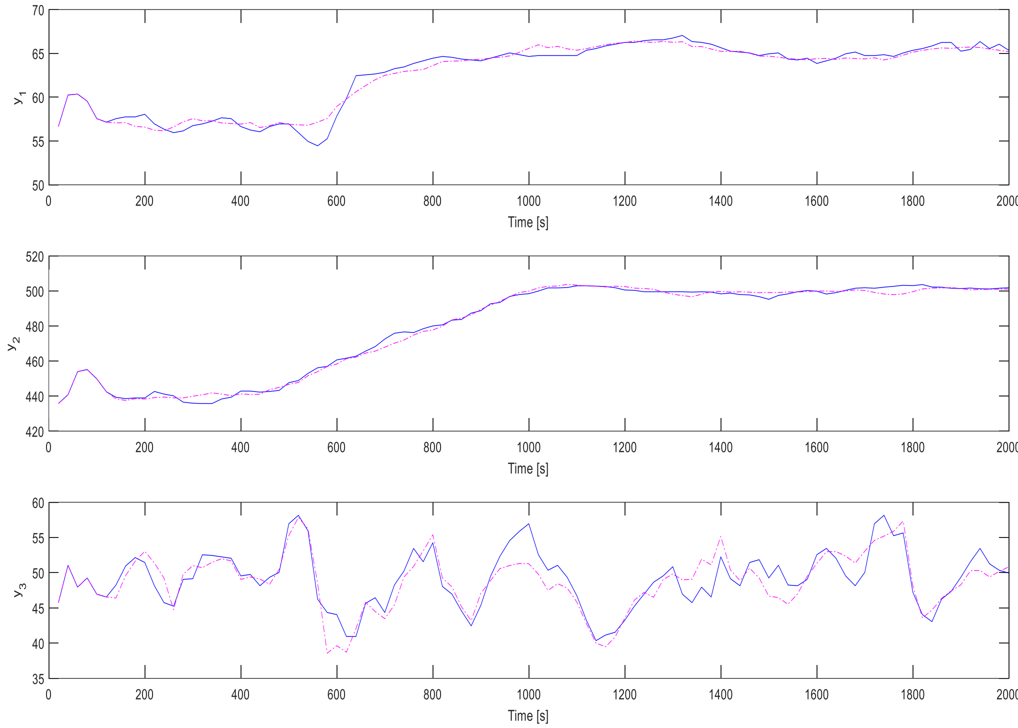

Fig. 4-1: Model identification validation graph

The model validation graph is shown in figure 4.1. It indicates the comparison of the identified model output graph (red line) with the validation output data (blue line). The terms y_1, y_2 and y_3 indicates the outputs of biomass boiler which are pressure, temperature and drum level respectively.

For this thesis work the model identification has shown the following VAF value for each measured output.

For Temperature VAF $=$ 96.7249% with 2 clusters.

For Pressure VAF $=$ 99.23% with 2 clusters.

For Drum Level VAF $=$ 75% with 4 clusters.

The identified model can also validate by correlation between residuals (error) and inputs. The auto correlation of the error also used for validation. The correlation between these variables should be weak for acceptable model identification. For the validation process of biomass boiler, the following correlation values are obtained.

Correlation between E1&E2 =0.034701

Correlation between E1&E3 = 0.124333

Correlation between E2&E3 = -0.083

Correlation between E1&U1 = -0.08735

Correlation between E1&U2 = -0.08524

Correlation between E1&U3 = 0.01965

Correlation between E1&U4 = 0.10711

Correlation between E2&U1 = 0.106442

Correlation between E2&U2 = 0.040236

Correlation between E2&U3 = 0.070593

Correlation between E2&U4 = -0.19622

Correlation between E3&U1 = 0.194731

Correlation between E3&U2 = 0.178469

Correlation between E3&U3 = 0.031941

Correlation between E3&U4 = 0.02353

The auto correlation of each error is give as follows

E1(K) & E1(K-6) = 0.031322

E2(K) & E2(K-6) = -0.0996

E3(K) & E3(K-6) = 0.044254

Where E1 is the error between temperature model and system output.

E2 is the error between pressure model and system output.

E3 is the error between level model and system output.

Correlation values which are less than 0.2 indicate that there is weak correlation between variables while, correlation value greater than 0.2 indicates high correlation between variables. According to the model validation Temperature and Pressure model have good fitting but drum level model indicates less fitting than the other but it can be used for controller design.

4.3. Open loop Response

The open loop configuration does not monitor or measure the condition of its output signal since there is no feedback. Testing the open loop with a step input means to put the signal in the input of the process and observing its output. The open loop response of the boiler controlled variables (i.e. Pressure, Temperature and Level) is shown in Fig 4.3.

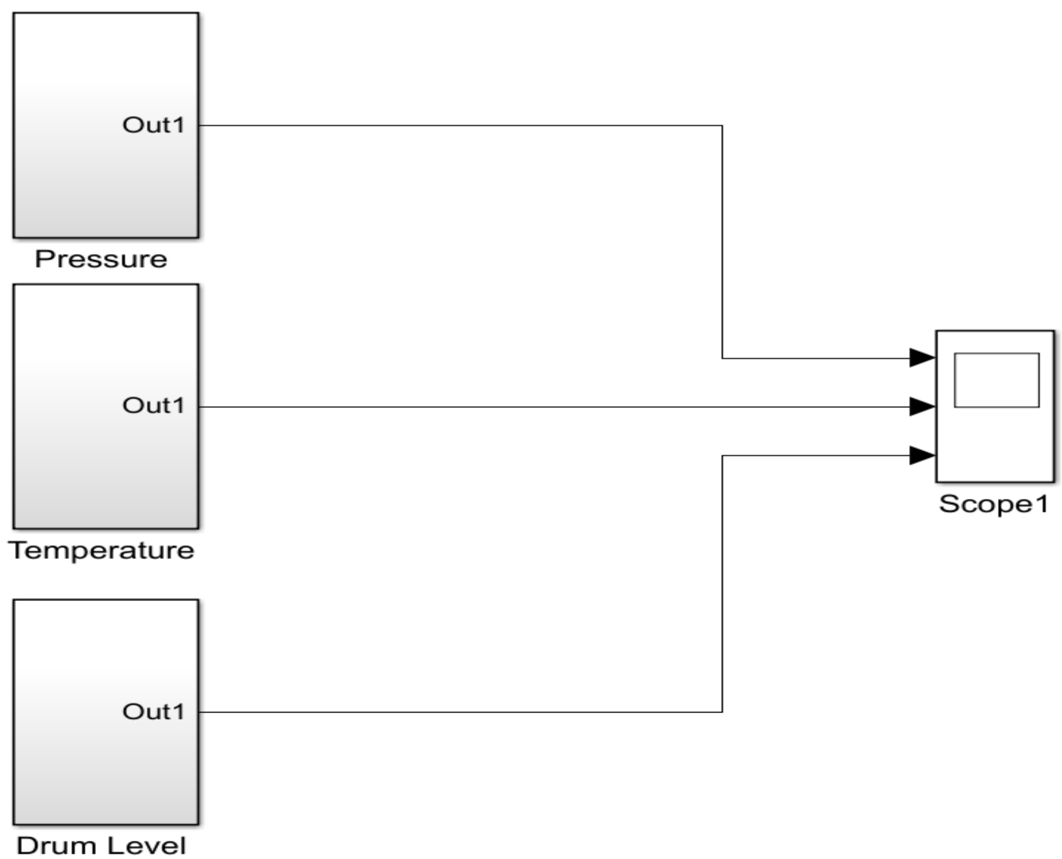

Fig. 4-2: Block diagram of open loop biomass boiler system

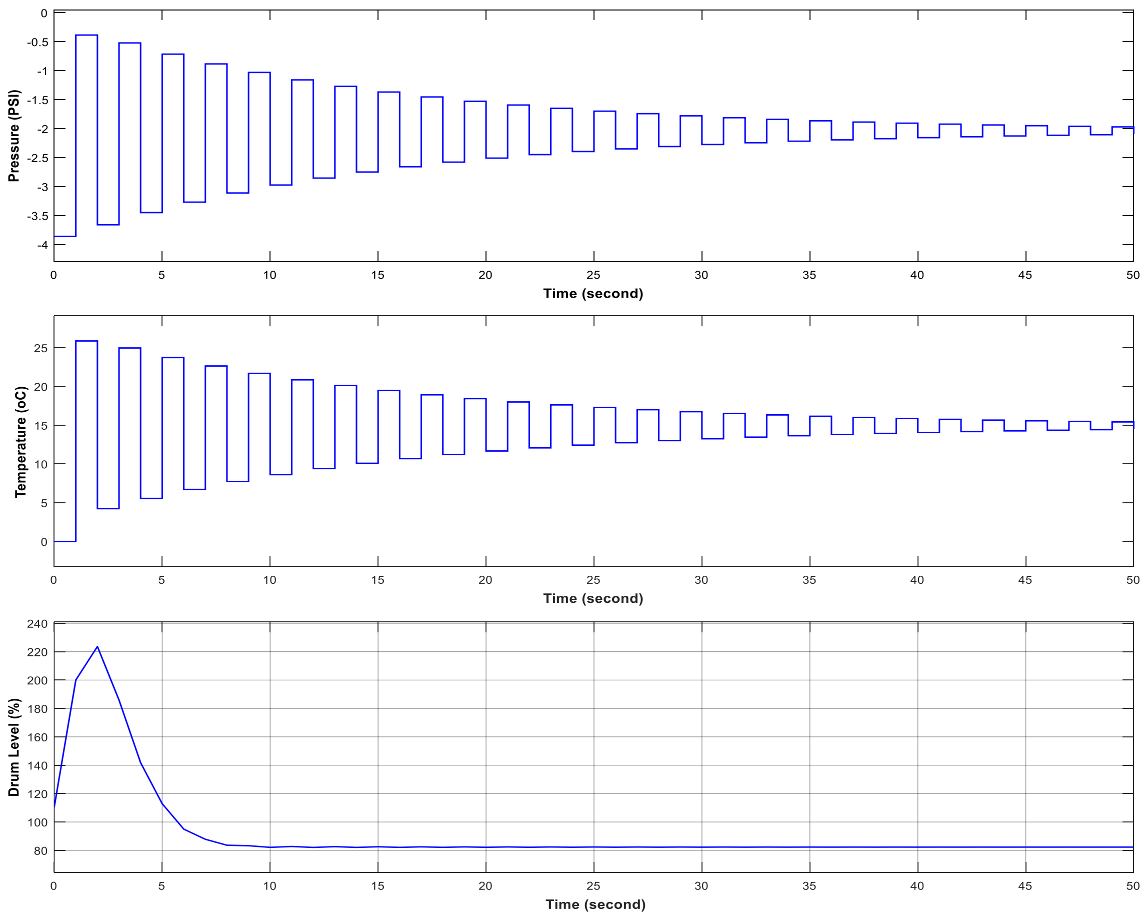

Fig. 4-3: Open loop response of biomass boiler system

4.4. Response of closed loop system with Model Predictive Controller

In this work the parameters of the MPC which are discussed in tuning section are tuned manually in MATLAB by using Model Predictive Controller Designer toolbox. The parameters of MPC which are tuned manually to get the closed loop response shown in figure 4.5 and figure 4.7 are $P = 36$ and $N_u = 5$. In this work the closed loop response of biomass boiler is shown in two parts. In the first part of closed loop simulation; the biomass boiler is divided in to three MISO systems which can able to control each controlled variable independently. In this case the cost function is minimized by considering only one output for each MISO system.

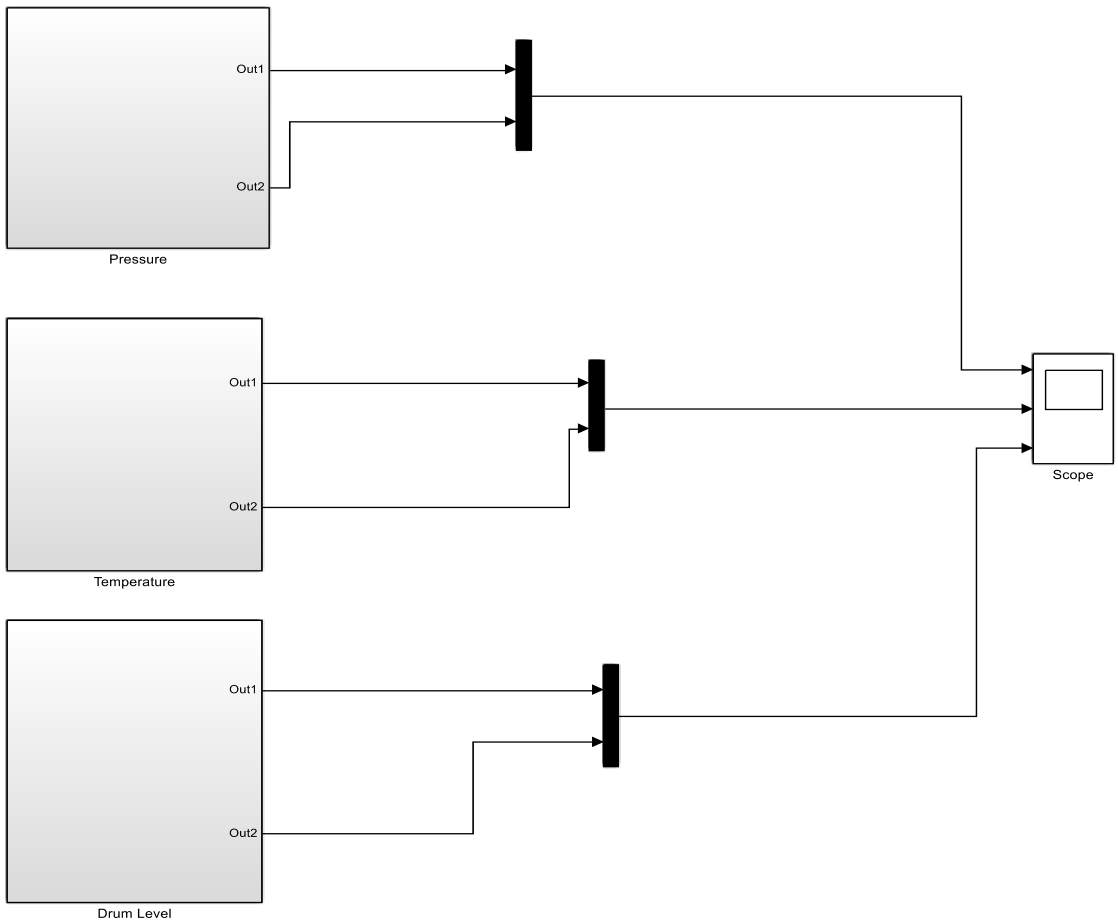

Fig. 4-4: Block diagram of MISO biomass boiler

The closed loop response of biomass boiler is shown in figure 4.5 and figure 4.7. It shows shorter settling time and small overshoots with small weights of input change rate and output as compared with the previous works which is discussed in table 4.2. The response of MISO and MIMO system performance characteristics are presented in table 4.1. In both responses the overshoot of drum level at starting time is high due to the effect of the responses of temperature and pressure (nominal values) until the model predictive controller take action to adjust it.

The second part of the simulation shows the overall MIMO biomass boiler system with single model predictive controller without expanding it as 3 MISO systems. In this case the cost function is computed by considering all three outputs and input increments to find the optimal solutions.

Table 4-1: Comparisons of MISO system and MIMO system characteristics

Performance characteristics	MISO system			MIMO system		
	Pressure	Temperature	Level	Pressure	Temperature	Level
Rise time(second)	3.36	1.257	-	2.349	0.8	-
Settling time(second)	7	5	13	5	4	7
Overshoot (%)	0.505	0.39	0.46	0.214	1.531	0.74
Input weight	0.02	0.067	0.1	0.02	0.02	0.02
Output weight	1.49	1.49	1	1.95	1.95	1.95

Since the cost function is different; the control performance of MISO system is not the same as MIMO system of biomass boiler. When the biomass boiler is controlled as single MIMO system; the level and pressure shows good settling time and overshoot, but the temperature shows higher overshoot than that of MISO system control.

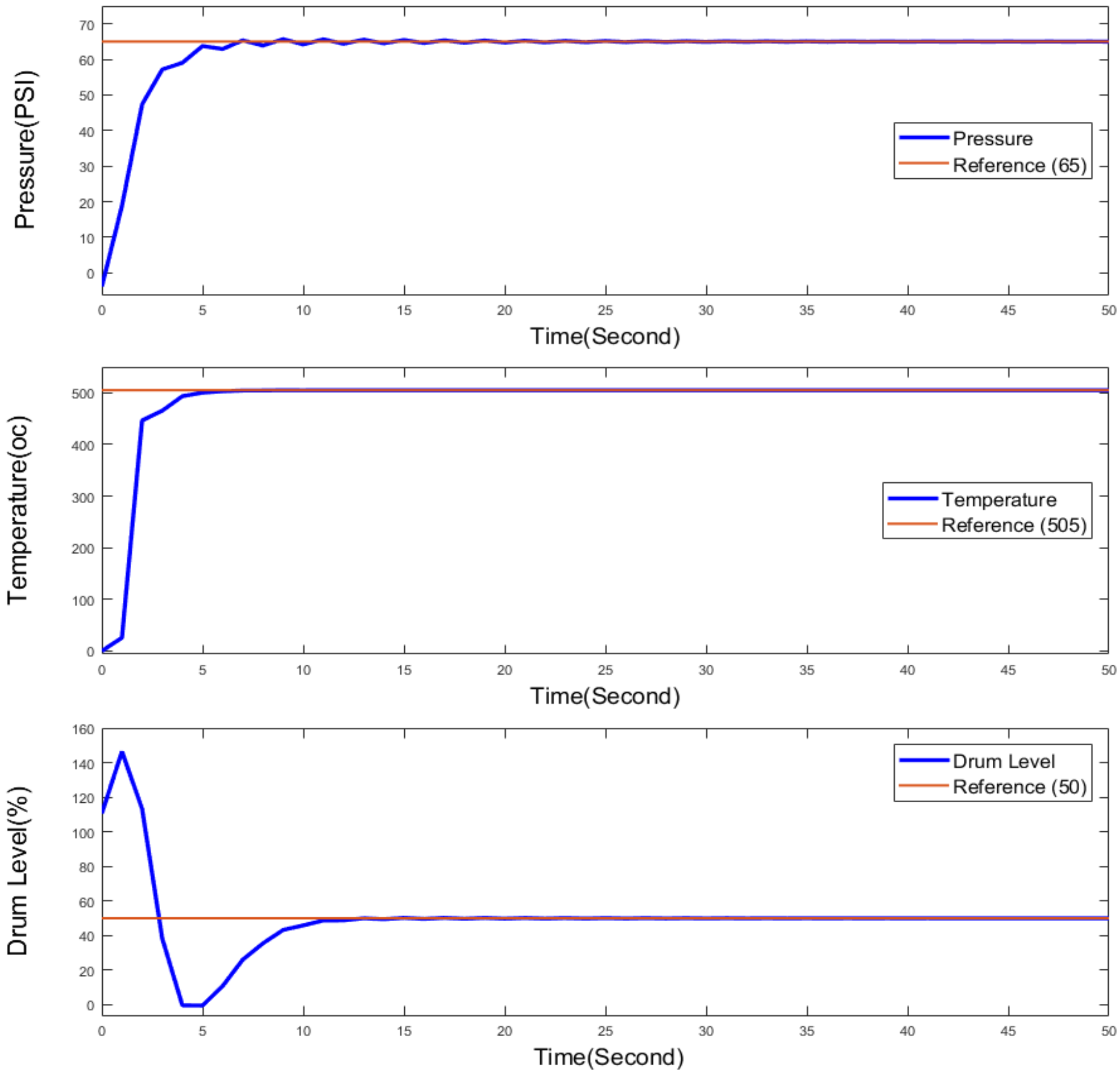

Fig. 4-5: Response of biomass boiler when it is controlled as MISO system

The response of MIMO biomass boiler is presented in the figure 4.9. Generally, MPC shows good performance in MIMO system control of Biomass boiler; because it performs control calculation based on the increments of inputs for all outputs at the same time with one cost function. Due to this the control action is based on the overall cost function caused by the summation of errors and increments in inputs.

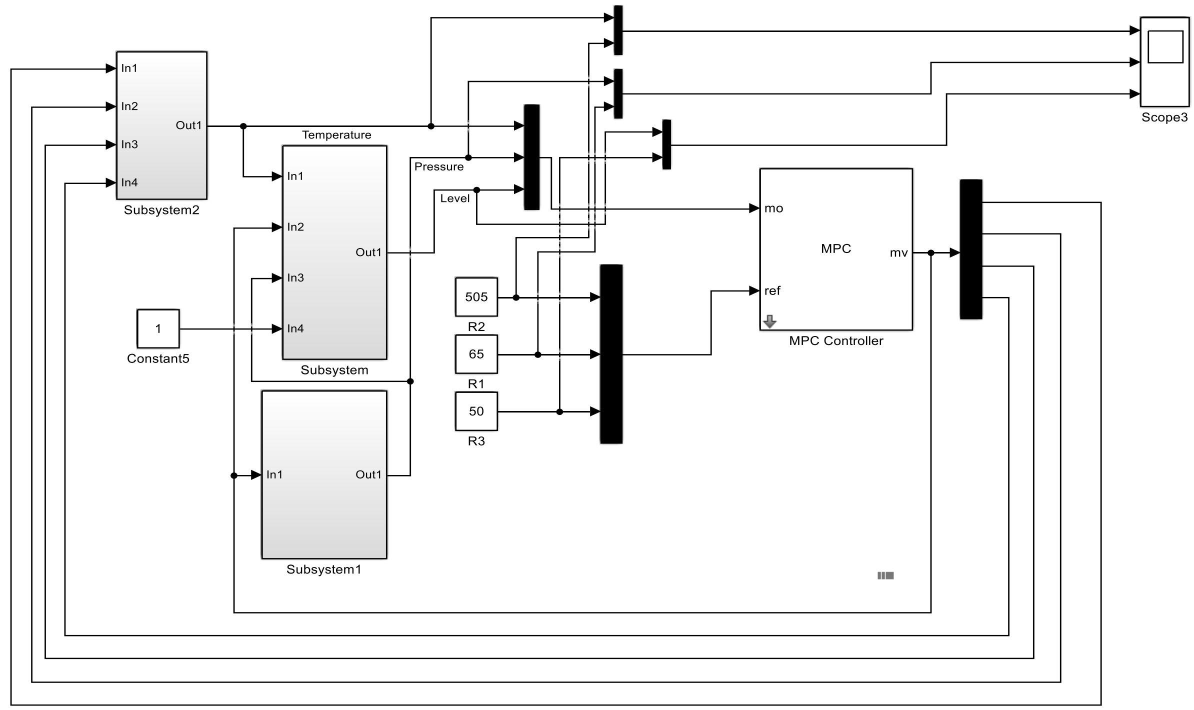

Fig. 4-6: Block diagram of biomass boiler when it is controlled as MIMO system

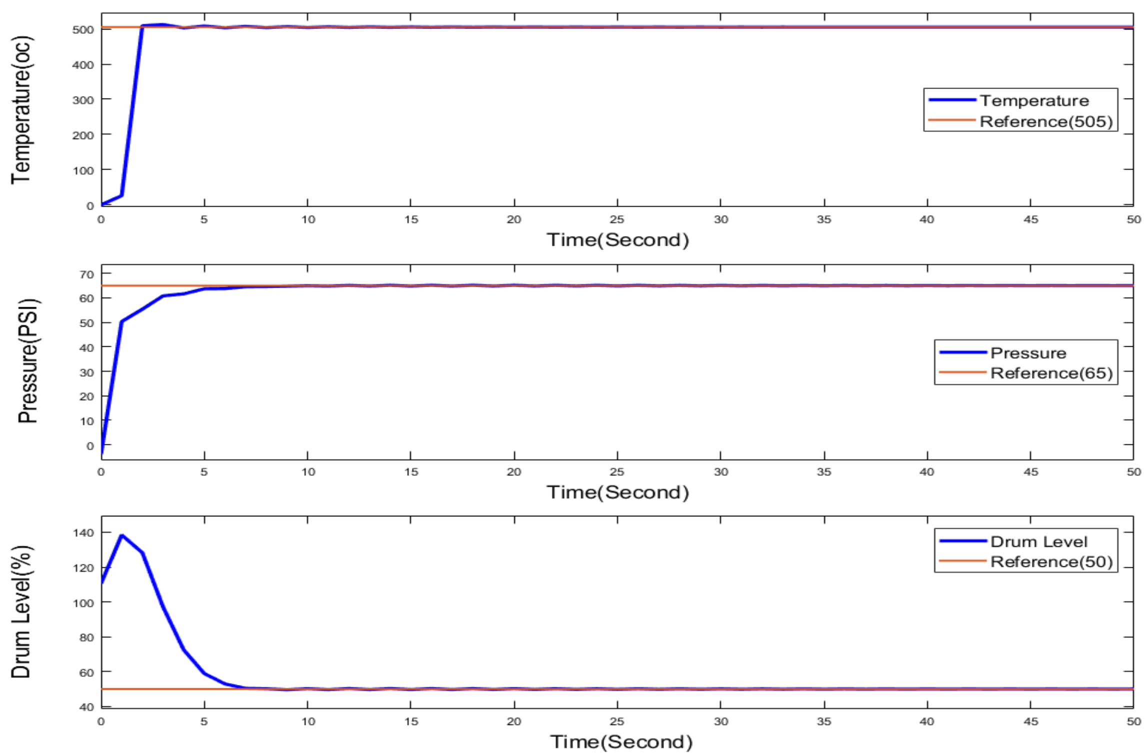

Fig. 4-7: Response of biomass boiler when it is controlled as MIMO system

The results which are obtained from this work shows shorter settling time, smaller overshoot and smaller steady state error than the current controlling mechanism and previous works. This is shown in the table 4.2. The current control strategy in Wenji-Shoa sugar factory biomass boiler is distributed control system which not fully automated and the responses doesn’t track the references. The previous work done by Michael Blanco uses ARX model for MPC which is obtained by system identification has shown in figure 4.8 [43]. It considers drum pressure and drum level as controlled variables but, this work considers temperature also as output in addition to the above variables.

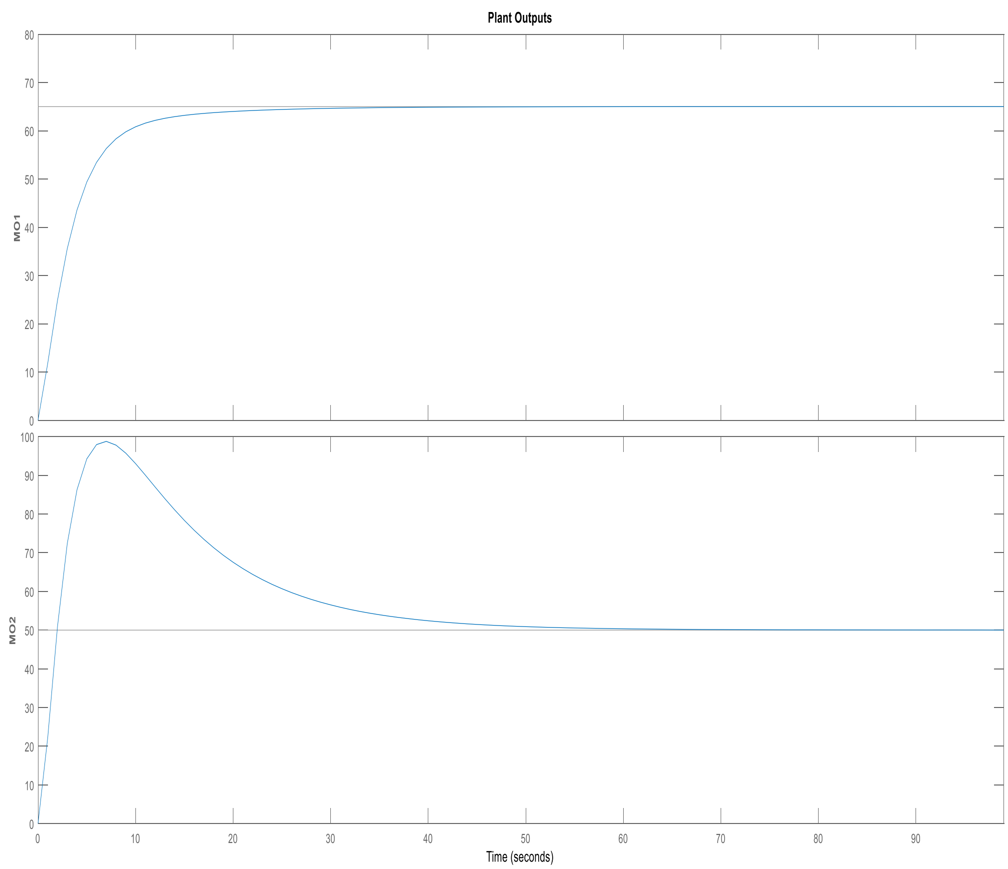

Fig. 4-8: Plant output of previous work

Table 4-2: Comparisons of previous work and this work

Performance characteristics	Previous work		This work	
	Pressure	Drum Level	Pressure	Drum Level
Rise time	8	1.81	2.34	0.93
Overshoot	0	97.6	0.214	0.66
Settling time	18.2	48.7	5	7
Error	0	0.1	0	0
Input weight	0.1,0.1,0.1,0.1	0.1,0.1,0.1,0.1	0.02,0.02,0.02,0.02	0.02,0.02,0.02,0.02
Output weight	15	2	1.5	1.9

Kortela also do his work on model predictive control for bio grate boiler using dynamic model of the bio grate boiler [34]. He considers pressure and steam power as output variables and he can enhance the settling time from 1.5 hour to two minutes, but this work enhances it to 7 seconds with the Takagi-Sugeno fuzzy model and can reduce the weighting factors of the inputs and outputs as shown in the table 4.1.

Chapter Five

5. Conclusions and Recommendations

5.1. Conclusions

In this work a fuzzy model predictive control mechanism for Biomass Boiler is done. This was done by finding the Takagi Sugeno fuzzy model for the biomass boiler by using fuzzy identification and then linearized by using global instantaneous linearization method. Pressure, Temperature and Drum Level are chosen as controlled variable. These variables in Biomass Boiler are nonlinear and time varying. The biomass boiler is MIMO system and there is high interaction between inputs and outputs. That makes model predictive controller a suitable control mechanism for the proposed system. To model these variables FMID (fuzzy modeling and identification) tool box is used. After the linearization the model predictive controller is designed and tuned automatically using MATLAB MPC designer toolbox.

The simulation carried out to track the reference values 65Kg/s, 505^{o}c and 50% for pressure, temperature and drum level respectively. The proposed control performance is achieved with model predictive controller. The simulation results are tested with MIMO and MISO system configuration. Good performance is achieved with MIMO since the cost function is the summation of all errors in the system. The parameters of the controller were tuned manually based on the requirements for each variables depending on the response of each controlled variable. The tuned parameters for the Model Predictive Controller which have shown good response were prediction horizon$(P) = 36$, control horizon$(M) = 5$ and the sampling time 1 second. The simulation result shows very fast rising and settling time and also an acceptable overshoot. While the current control strategy shows slow settling time and increment and decrement in the response of each controlled variables.

5.2. Recommendations

As it is shown in the result and discussion part model predictive control and fuzzy model show a better result for pressure and temperature as compared to that of the conventional one. In the identification session the steady state data is used for modeling and it is validated by simulation only therefore, anyone can take it and implement. The drum level can be identified by other method to get good model accuracy or may use model free control mechanism to control it.

In this work the controller is designed for the globally linearized fuzzy model. As future work, the Biomass Boiler control can be extended to nonlinear model predictive control. Since NMPC is more effective than linear model predictive controller for nonlinear and more interactive systems like Biomass Boiler. The tuning method also can be extended to automatic tuning by using particle swarm optimization or genetic algorithms.

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Appendices

Appendix A: Takagi-Sugeno Fuzzy model of Biomass Boiler

Output1(pressure):

Rules:

Rule1: **If** $y\,1(k-1)$ is $A\,11$ **and** $y\,1(k-2)$ is $A\,12$ **and** $u\,1(k-1)$ is $A\,13$ **and** $u\,1(k-2)$ is $A\,14$ **and** $u\,2(k-1)$ is $A\,15$ **and** $u\,2(k-2)$ is $A\,16$ **and** $u\,3(k-1)$ is $A\,17$ **and** $u\,3(k-2)$ is $A\,18$ **and** $u\,4(k-1)$ is $A\,19$ **and** $u\,4(k-2)$ is $A\,110$ **then**

$y\,1(k) = 1.4055\,y\,1(k-1) - 0.59y\,1(k-2) - 0.0744u\,1(k-1) + 0.1309u\,1(k-2) - 0.0207\,u\,2(k-1) + 0.0268u\,2(k-2) - 0.0072\,u\,3(k-1) + 0.0135u\,3(k-2) + 0.0615u\,4(k-1) + 0.0451u\,4(k-2) - 2.6258$

Rule2: **If** $y\,1(k-1)$ is $A\,21$ **and** $y\,1(k-2)$ is $A\,22$ **and** $u\,1(k-1)$ is $A\,23$ **and** $u\,1(k-2)$ is $A\,24$ **and** $u\,2(k-1)$ is $A\,25$ **and** $u\,2(k-2)$ is $A\,26$ ***and*** $u\,3(k-1)$ is $A\,27$ **and** $u\,3(k-2)$ is $A\,28$ **and** $u\,4(k-1)$ is $A\,29$ **and** $u\,4(k-2)$ is $A\,210$ **then**

$y\,1(k) = 0.5488y\,1(k-1) + 0.3806y\,1(k-2) + 0.0015u\,1(k-1) - 0.0013u\,1(k-2) + 0.0209u\,2(k-1) - 0.0012u\,2(k-2) - 0.00035842u\,3(k-1) + 0.015u\,3(k-2) - 0.0351u\,4(k-1) - 0.0285u\,4(k-2) - 4.8332$

Output2(Temperature):

Rules:

Rule1: **If** $y2(k-1)$ is $A11$ **and** $y2(k-2)$ is $A12$ **and** $u1(k-1)$ is $A13$ **and** $u1(k-2)$ is $A14$ **and** $u2(k-1)$ is $A15$ **and** $u2(k-2)$ is $A\,16$ **and** $u\,3(k-1)$ is $A17$ **and** $u3(k-2)$ is $A18$ **and** $u4(k-1)$ is $A19$ **and** $u4(k-2)$ is $A110$ **then**

$Y2(k) = 1.5314\, y2(k-1) - 0.6437 y2(k-2) - 0.2255 u1(k-1) + 0.338 u1(k-2) - 0.0055$ $u2(k-1) + 0.0022 u2(k-2) + 0.2584\, u3(k-1) - 0.0506 u3(k-2) + 0.2705 u4(k-1) -$ $0.2009 u4(k-2) + 45.8608$

Rule2: **If** $y2(k-1)$ is $A\,21$ **and** $y2(k-2)$ is $A\,22$ **and** $u\,1(k-1)$ is $A\,23$ **and** $u\,1(k-2)$ is $A\,24$ **and** $u2(k-1)$ is $A25$ **and** $u2(k-2)$ is $A26$ ***and*** $u3(k-1)$ is $A27$ **and** $u3(k-2)$ is $A28$ **and** $u4(k-1)$ is $A29$ **and** $u4(k-2)$ is $A210$ **then**

$y2(k) = 0.5052 y2(k-1) + 0.2909 y2(k-2) - 0.0491 u1(k-1) + 0.0758 u1(k-2) +$ $0.1576 u2(k-1) - 0.0101\, u2(k-2) - 0.0436\, u3(k-1) - 0.0368 u3(k-2) - 0.1894$ $u4(k-1) + 0.3081 u4(k-2) + 16.7559$

Output3 (Drum Level):

Rules:

Rule1: **If** $y\,1(k-1)$ is $A\,11$ **and** $y\,2(k-1)$ is $A\,12$ **and** $y\,3(k-1)$ is $A\,13$ **and** $y\,3(k-2)$ is $A\,14$ **and** $u\,1(k-1)$ is $A\,15$ **and** $u\,1(k-2)$ is $A\,16$ **and** $u\,2(k-1)$ is $A\,17$ **and** $u\,2(k-2)$ is $A\,18$ **and** $u\,3(k-1)$ is $A\,19$ **and** $u\,3(k-2)$ is $A\,110$ **and** $u\,4(k-1)$ is $A\,111$ **and** $u\,4(k-2)$ is $A112$ **then**

$y\,3(k) = -3.5\,741 y\,1(k-1) + 0.87\, y\,2(k-1) - 0.43\, y\,3(k-1) + 0.72\, y\,3(k-2) + 0.6161$ $u\,1(k-1) - 0.7962\, u\,1(k-2) + 0.812\, u\,2(k-1) - 0.2939\, u\,2(k-2) - 1.2145 u\,3(k-1) +$ $1.1\, u\,3(k-2) - 0.4726\, u\,4(k-1) + 2.2534 + u\,4(k-2) - 97.02$

Rule2: **If** $y\,1(k-1)$ is $A\,21$ **and** $y\,2(k-1)$ is $A\,22$ **and** $y\,3(k-1)$ is $A\,23$ **and** $y\,3(k-2)$ is $A\,24$ **and** $u\,1(k-1)$ is $A\,25$ **and** $u\,1(k-2)$ is $A\,26$ **and** $u\,2(k-1)$ is $A\,27$ **and** $u\,2(k-2)$ is $A\,28$ **and** $u\,3(k-1)$ is $A\,29$ **and** $u\,3(k-2)$ is $A\,210$ **and** $u\,4(k-1)$ is $A\,211$ **and** $u\,4(k-2)$ is $A212$ **then**

$y\,3(k) = 0.4431\,y\,1(k-1) + 0.1702\,y\,2(k-1) + 1.1875 y\,3(k-1) - 0.796\,y\,3(k-2) - 1.3694\,u1(k-1) + 1.4533\,u\,1(k-2) - 0.274\,u\,2(k-1) - 0.1039\,u\,2(k-2) + 0.3888\,u\,3(k-1) - 1.8267 u\,3(k-2) + 1.623 u\,4(k-1) - 2.7371 u\,4(k-2) + 129.4029$

Rule3: **If** $y\,1(k-1)$ is $A\,31$ **and** $y\,2(k-1)$ is $A\,32$ **and** $y\,3(k-1)$ is $A\,33$ **and** $y\,3(k-2)$ is $A\,34$ **and** $u\,1(k-1)$ is $A\,35$ **and** $u\,1(k-2)$ is $A\,36$ **and** $u\,2(k-1)$ is $A\,37$ **and** $u\,2(k-2)$ is $A\,38$ **and** $u\,3(k-1)$ is $A\,39$ **and** $u\,3(k-2)$ is $A\,310$ **and** $u\,4(k-1)$ is $A\,311$ **and** $u4(k-2)$is$A312$**then**

$y\,3(k) = -0.0331 y\,1(k-1) - 0.9515\,y\,2(k-1) + 0.8654\,y\,3(k-1) - 0.1465\,y\,3(k-2) - 0.0017\,u1(k-1) - 0.0131 u\,1(k-2) - 1.3152 u\,2(k-1) + 1.9041\,u\,2(k-2) - 0.8688 u\,3(k-1) + 0.8002 u3(k-2) + 0.9916\,u\,4(k-1) - 0.0304\,u\,4(k-2) + 122.7051$

Rule4: **If** $y\,1(k-1)$ is $A\,41$ **and** $y\,2(k-1)$ is $A\,42$ **and** $y\,3(k-1)$ is $A\,43$ **and** $y\,3(k-2)$ is $A\,44$ **and** $u\,1(k-1)$ is $A\,45$ **and** $u\,1(k-2)$ is $A\,46$ **and** $u\,2(k-1)$ is $A\,47$ **and** $u\,2(k-2)$ is $A\,48$ **and** $u\,3(k-1)$ is $A\,49$ **and** $u\,3(k-2)$ is $A\,410$ **and** $u\,4(k-1)$ is $A\,411$ **and** $u\,4(k-2)$is$A412$**then**

$y\,3(k) = -0.9989\,y\,1(k-1) - 0.159\,y\,2(k-1) + 1.286\,y\,3(k-1) - 0.4473\,y\,3(k-2) + 0.2706\,u1(k-1) - 0.3163\,u\,1(k-2) + 0.3688\,u\,2(k-1) - 0.6089\,u\,2(k-2) + 0.7669 u\,3(k-1) + 0.2\,u3(k-2) - 1.2769 u\,4(k-1) + 0.8637\,u\,4(k-2) + 246.48$

Appendix B: MATLAB code for Biomass Boiler Model identification

```
load data;
load input;
load output;
data=iddata(y,u,1);
data.inputname={'Water Flow';'Fuel Flow';'Air Flow1';'Air
Flow2'};
data.outputname={'Pressure';'Temperature';'Drum Level'}
% generate a fuzzy model for biomass boiler
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% define constants
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
c = [2 2 4];          % n umber of clusters
m = 2.2;        % fuzziness parameter
tol = 0.0001;     % termination criterion
Ts = 1;       % sample time [s]
FMtype = [1 1 1];
Ny =[2 0 0;0 2 0;1 1 2];       % denominator order
Nu = [2 2 2 2;2 2 2 2;2 2 2 2];  % numerator orders
Nd = [1 1 1 1;1 1 1 1;1 1 1 1];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% identification data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Input=U;
output=y;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% validation data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ue=[data(:,1) data(:,2) data(:,3) data(:,4)];
ye=[data(:,5) data(:,6) data(:,7)];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

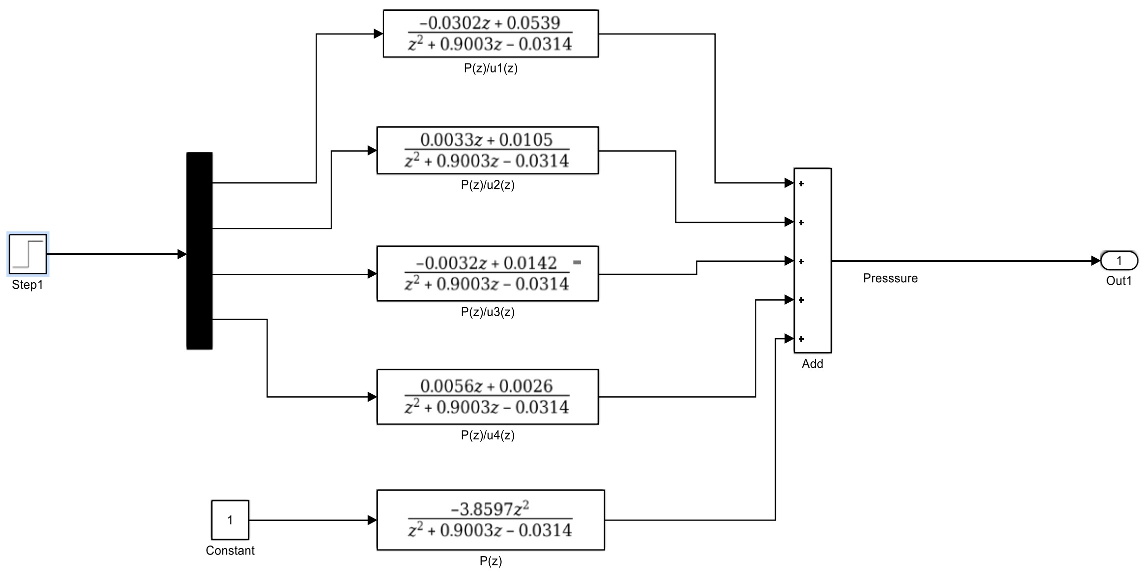
```
% make fuzzy model by means of fuzzy clustering
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Dat.U = u; Dat.Y = y; Dat.Ts = Ts;
FM.c = c; FM.m = m; FM.ante = FMtype; FM.tol = tol;
FM.Ny = Ny; FM.Nu = Nu; FM.Nd = Nd;
[FM,Part] = fmclust(Dat,FM);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% simulate the fuzzy model for validation data
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[ym,VAF,dof,yl,ylm] = fmsim(ue,ye,FM,[],[],1);
VAF
[FM,dof]=fmest(FM,Dat)
fm2tex(FM,'fuzzymeskerem27')
[DOF,X] = fmdof(u,y,FM)
```

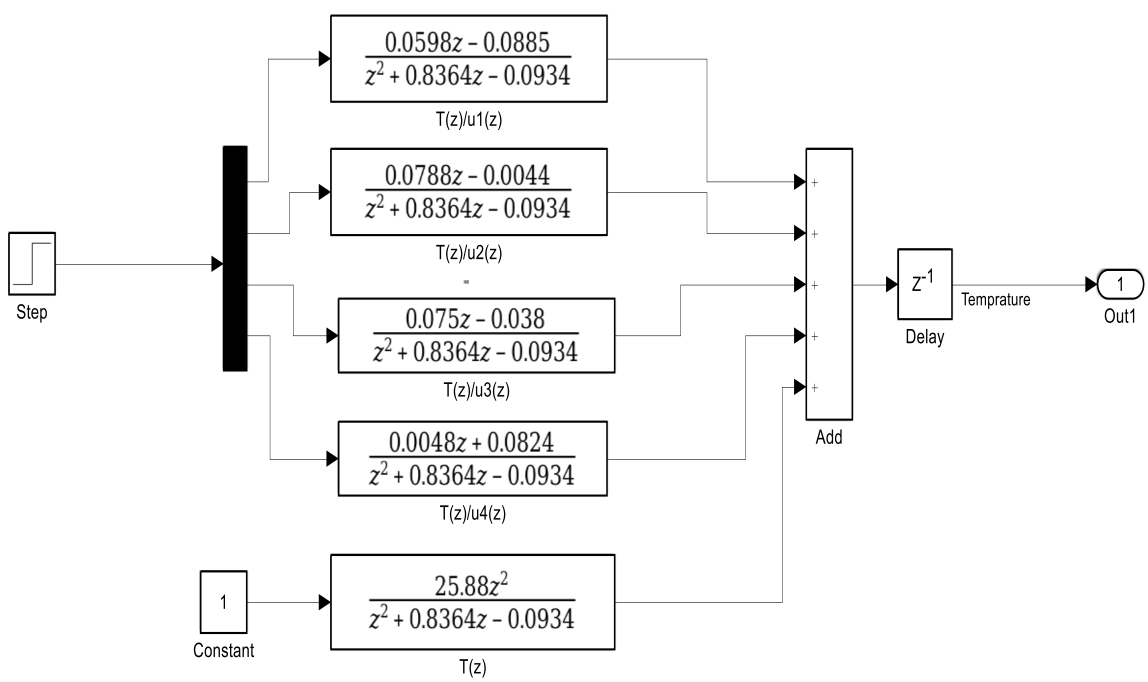
Appendix C: MATLAB code for Computing Prediction matrices

```
A=[1 0 0 0.9003 0 0 -0.0314 0 0;
    0 1 0 0 0.8364 0 0 -0.0934 0;
    0 0 1 -0.9681 -0.0238 -0.7763 0 0 0.2087];
B=[-0.0302 0.0033 -0.0032 0.0056 0.0539 0.0105 0.0142 0.0026;
    0.0598 0.0788 0.075 0.0048 -0.088 -0.0044 -0.038 0.0824;
 -0.1388 -0.1769 -0.1402 0.1689 0.1043 0.1588 0.0072 0.0345];
ny=36;
[H,P,Q]=mpc_predmat(A,B,ny)
```

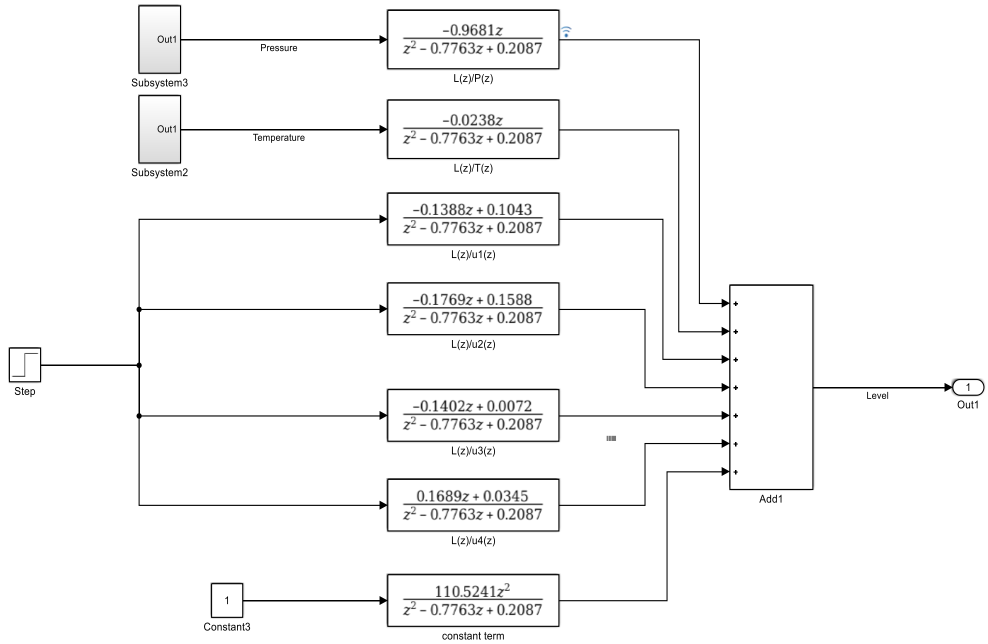
Appendix D: Details of subsystems in Fig. 4.2, Fig. 4.4 and Fig.4.6



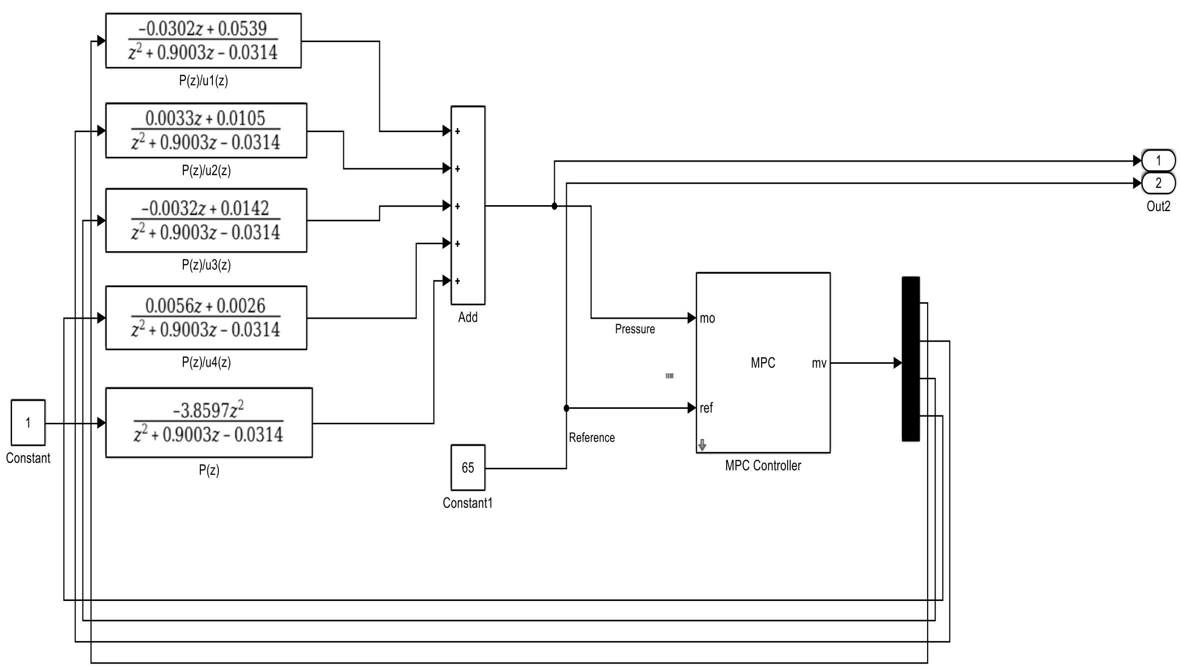
Pressure in fig. 4.2 and subsystem1 in fig. 4.6



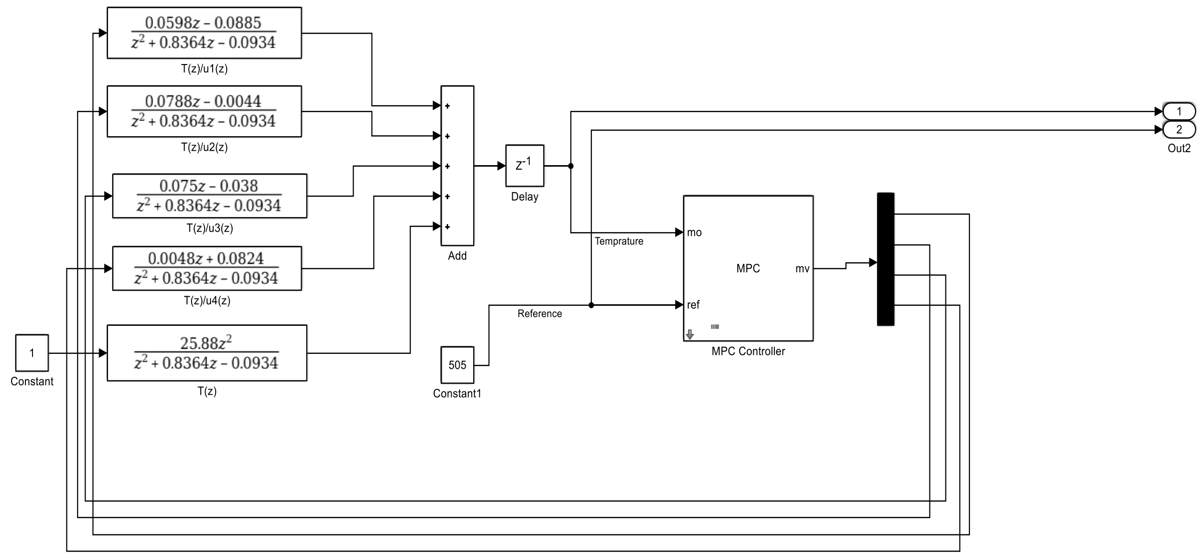
Temperature in fig.4.2 and subsystem2 in fig. 4.6



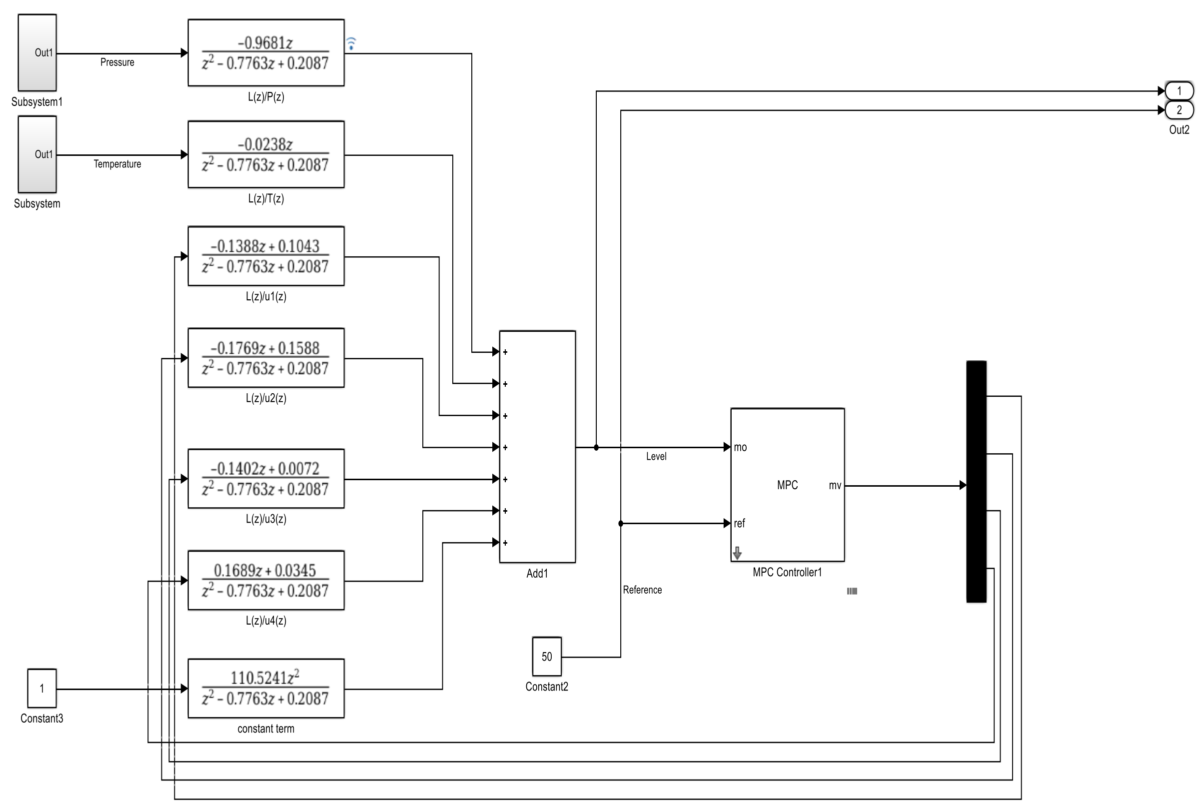
Drum Level in fig. 4.2 and subsystem in fig. 4.6



Pressure subsystem in fig.4.4



Temperature subsystem in fig 4.4



Drum Level subsystem in fig. 4.4